

# Iterated proportional fitting procedure and infinite products of stochastic matrices

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## Abstract

The iterative proportional fitting procedure (IPFP), introduced in 1937 by Kruijthof, aims to adjust the elements of an array to satisfy specified row and column sums. Thus, given a rectangular non-negative matrix  $X_0$  and two positive marginals  $a$  and  $b$ , the algorithm generates a sequence of matrices  $(X_n)_{n \geq 0}$  starting at  $X_0$ , supposed to converge to a biproportional fitting, that is, to a matrix  $Y$  whose marginals are  $a$  and  $b$  and of the form  $Y = D_1 X_0 D_2$ , for some diagonal matrices  $D_1$  and  $D_2$  with positive diagonal entries.

When a biproportional fitting does exist, it is unique and the sequence  $(X_n)_{n \geq 0}$  converges to it at an at least geometric rate. More generally, when there exists some matrix with marginal  $a$  and  $b$  and with support included in the support of  $X_0$ , the sequence  $(X_n)_{n \geq 0}$  converges to the unique matrix whose marginals are  $a$  and  $b$  and which can be written as a limit of matrices of the form  $D_1 X_0 D_2$ .

In the opposite case (when there exists no matrix with marginals  $a$  and  $b$  whose support is included in the support of  $X_0$ ), the sequence  $(X_n)_{n \geq 0}$  diverges but both subsequences  $(X_{2n})_{n \geq 0}$  and  $(X_{2n+1})_{n \geq 0}$  converge.

In the present paper, we use a new method to prove again these results and determine the two limit-points in the case of divergence. Our proof relies on a new convergence theorem for backward infinite products  $\cdots M_2 M_1$  of stochastic matrices  $M_n$ , with diagonal entries  $M_n(i, i)$  bounded away from 0 and with bounded ratios  $M_n(j, i)/M_n(i, j)$ . This theorem generalizes Lorenz' stabilization theorem.

We also provide an alternative proof of Touric and Nedić's theorem on backward infinite products of doubly-stochastic matrices, with diagonal entries bounded away from 0. In both situations, we improve slightly the conclusion, since we establish not only the convergence of the sequence  $(M_n \cdots M_1)_{n \geq 0}$ , but also its finite variation.

Keywords: infinite products of stochastic matrices - contingency matrices - distributions with given marginals - iterative proportional fitting - relative entropy - I-divergence.

MSC Classification: 15B51 - 62H17 - 62B10 - 68W40.

## 1 Introduction

### 1.1 The iterative proportional fitting procedure

Fix two integers  $p \geq 2$ ,  $q \geq 2$  (namely the sizes of the matrices to be considered) and two vectors  $a = (a_1, \dots, a_p)$ ,  $b = (b_1, \dots, b_q)$  with positive components such that  $a_1 + \cdots + a_p = b_1 + \cdots + b_q = 1$  (namely the target marginals). We assume that the common value of the sums  $a_1 + \cdots + a_p$  and  $b_1 + \cdots + b_q$  is 1 for convenience only, to enable probabilistic interpretations, but this is not a true restriction.

We introduce the following notations for any  $p \times q$  real matrix  $X$ :

$$X(i, +) = \sum_{j=1}^q X(i, j), \quad X(+, j) = \sum_{i=1}^p X(i, j), \quad X(+, +) = \sum_{i=1}^p \sum_{j=1}^q X(i, j),$$

and we set  $R_i(X) = X(i, +)/a_i$ ,  $C_j(X) = X(+, j)/b_j$ .

The IPFP has been introduced in 1937 by Kruithof [8] to estimate telephone traffic between central stations. This procedure starts from a  $p \times q$  non-negative matrix  $X_0$  such that the sum of the entries on each row or column is positive (so  $X_0$  has at least one positive entry on each row or column) and works as follows.

- For each  $i \in [1, p]$ , divide the row  $i$  of  $X_0$  by the positive number  $R_i(X_0)$ . This yields a matrix  $X_1$  satisfying the same assumptions as  $X_0$  and having the desired row-marginals.
- For each  $j \in [1, q]$ , divide the row  $j$  of  $X_1$  by the positive number  $C_j(X_1)$ . This yields a matrix  $X_2$  satisfying the same assumptions as  $X_0$  and having the desired column-marginals.
- Repeat the operations above starting from  $X_2$  to get  $X_3, X_4$ , and so on.

Denote by  $\mathcal{M}_{p,q}(\mathbf{R}_+)$  the set of all  $p \times q$  matrices with non-negative entries, and consider the following subsets:

$$\begin{aligned} \Gamma_0 &:= \{X \in \mathcal{M}_{p,q}(\mathbf{R}_+) : \forall i \in [1, p], X(i, +) > 0, \forall j \in [1, q], X(+, j) > 0\}, \\ \Gamma_1 &:= \{X \in \Gamma_0 : X(+, +) = 1\} \\ \Gamma_R &:= \Gamma(a, *) = \{X \in \Gamma_0 : \forall i \in [1, p], X(i, +) = a_i\}, \\ \Gamma_C &:= \Gamma(*, b) = \{X \in \Gamma_0 : \forall j \in [1, q], X(+, j) = b_j\}, \\ \Gamma &:= \Gamma(a, b) = \Gamma_R \cap \Gamma_C. \end{aligned}$$

For every integer  $m \geq 1$ , denote by  $\Delta_m$  the set of all  $m \times m$  diagonal matrices with positive diagonal entries.

The IPFP consists in applying alternatively the transformations  $T_R : \Gamma_0 \rightarrow \Gamma_R$  and  $T_C : \Gamma_0 \rightarrow \Gamma_C$  defined by

$$T_R(X)(i, j) = R_i(X)^{-1} X(i, j) \text{ and } T_C(X)(i, j) = C_j(X)^{-1} X(i, j).$$

Note that  $\Gamma_R$  and  $\Gamma_C$  are subsets of  $\Gamma_1$  and are closed subsets of  $\mathcal{M}_{p,q}(\mathbf{R}_+)$ . Therefore, if  $(X_n)_{n \geq 0}$  converges, its limit belongs to the set  $\Gamma$ . Furthermore, by construction, the matrices  $X_n$  belong to the set

$$\begin{aligned} \Delta_p X_0 \Delta_q &= \{D_1 X_0 D_2 : D_1 \in \Delta_p, D_2 \in \Delta_q\} \\ &= \{(\alpha_i X_0(i, j) \beta_j) : (\alpha_1, \dots, \alpha_p) \in (\mathbf{R}_+^*)^p, (\beta_1, \dots, \beta_q) \in (\mathbf{R}_+^*)^q\}. \end{aligned}$$

In particular, the matrices  $X_n$  have by construction the same support, where the support of a matrix  $X \in \mathcal{M}_{p,q}(\mathbf{R}_+)$  is defined by

$$\text{Supp}(X) = \{(i, j) \in [1, p] \times [1, q] : X(i, j) > 0\}.$$

Therefore, for every limit point  $L$  of  $(X_n)_{n \geq 0}$ , we have  $\text{Supp}(L) \subset \text{Supp}(X_0)$  and this inclusion may be strict. In particular, if  $(X_n)_{n \geq 0}$  converges, its limit belongs to the set

$$\Gamma(X_0) := \Gamma(a, b, X_0) = \{S \in \Gamma : \text{Supp}(S) \subset \text{Supp}(X_0)\}.$$

When the set  $\Gamma(X_0)$  is empty, the sequence  $(X_n)_{n \geq 0}$  cannot converge, and no precise behavior was established until 2013, when Gietl and Reffel showed that both subsequences  $(X_{2n})_{n \geq 0}$  and  $(X_{2n+1})_{n \geq 0}$  converge.

In the opposite case, namely when  $\Gamma(a, b)$  contains some matrix with support included in  $X_0$ , various proofs of the convergence of  $(X_n)_{n \geq 0}$  are known (Bacharach [1] in 1965, Bregman [2] in 1967, Sinkhorn [12] in 1967, Csiszár [4] in 1975, Pretzel [10] in 1980 and others (see [3] and [11] to get an exhaustive review). Moreover, the limit can be described using some probabilistic tools that we introduce now.

## 1.2 Probabilistic interpretations and tools

At many places, we shall identify  $a, b$  and matrices  $X$  in  $\Gamma_1$  with the probability measures on  $[1, p]$ ,  $[1, q]$  and  $[1, p] \times [1, q]$  given by  $a(\{i\}) = a_i$ ,  $b(\{j\}) = b_j$  and  $X(\{(i, j)\}) = X(i, j)$ . Through this identification, the set  $\Gamma_1$  can be seen as the set of all probability measures on  $[1, p] \times [1, q]$  whose marginals charge every point; the set  $\Gamma$  can be seen as the set of all probability measures on  $[1, p] \times [1, q]$  having marginals  $a$  and  $b$ . This set is non-empty since it contains the probability  $a \otimes b$ .

The  $I$ -divergence, or Kullback-Leibler divergence, also called relative entropy, plays a key role in the study of the iterative proportional fitting algorithm. For every  $X$  and  $Y$  in  $\Gamma_1$ , the relative entropy of  $Y$  with respect to  $X$  is

$$D(Y||X) = \sum_{(i,j) \in \text{Supp}(X)} Y(i, j) \ln \frac{Y(i, j)}{X(i, j)} \text{ if } \text{Supp}(Y) \subset \text{Supp}(X),$$

and  $D(Y||X) = +\infty$  otherwise, with the convention  $0 \ln 0 = 0$ . Although  $D$  is not a distance, the quantity  $D(Y||X)$  measures in some sense how much  $Y$  is far from  $X$  since  $D(Y||X) \geq 0$ , with equality if and only if  $Y = X$ .

In 1968, Ireland and Kullback [7] gave an incomplete proof of the convergence of  $(X_n)_{n \geq 0}$  when  $X_0$  is positive, relying on the properties of the  $I$ -divergence. Yet, the  $I$ -divergence can be used to prove the convergence when the set  $\Gamma(X_0)$  is non-empty, and to determine the limit. The maps  $T_R$  and  $T_C$  can be viewed as  $I$ -projections on  $\Gamma_R$  and  $\Gamma_C$  in the sense that for every  $x \in \Gamma_0$ ,  $T_R(X)$  (respectively  $T_C(X)$ ) is the only matrix achieving the least upper bound of  $D(Y||X)$  over all  $X$  in  $\Gamma_R$  (respectively  $\Gamma_C$ ).

In 1975, Csiszár established (theorem 3.2 in [4]) that, given a finite collection of linear sets  $\mathcal{E}_1, \dots, \mathcal{E}_k$  of probability distributions on a finite set, and a distribution  $R$  such that  $\mathcal{E}_1 \cap \dots \cap \mathcal{E}_k$  contains some probability distribution which is absolutely continuous with regard to  $R$ , the sequence obtained from  $R$  by applying cyclically the  $I$ -projections on  $\mathcal{E}_1, \dots, \mathcal{E}_k$  converges to the  $I$ -projection of  $R$  on  $\mathcal{E}_1 \cap \dots \cap \mathcal{E}_k$ . This result applies to our context (the finite set is  $[1, p] \times [1, q]$ , the linear sets  $\mathcal{E}_1$  and  $\mathcal{E}_2$  are  $\Gamma_R$  and  $\Gamma_C$ ) and shows that if the set  $\Gamma = \Gamma_R \cap \Gamma_C$  contains some matrix with support included in  $X_0$ , then  $(X_n)_{n \geq 0}$  converges to the  $I$ -projection of  $X_0$  on  $\Gamma$ .

## 2 Old and new results

Since the behavior of the sequence  $(X_n)_{n \geq 0}$  depends only on the existence or the non-existence of elements of  $\Gamma$  with support equal to or included in  $\text{Supp}(X_0)$ , we state a criterion which determines in which case we are.

Consider two subsets  $A$  of  $[1, p]$  and  $B$  of  $[1, q]$  such that  $X_0$  is null on  $A \times B$ . Note  $A^c = [1, p] \setminus A$  and  $B^c = [1, q] \setminus B$ . Then for every  $S \in \Gamma(X_0)$ ,

$$a(A) = \sum_{i \in A} a_i = \sum_{(i,j) \in A \times B^c} S(i,j) \leq \sum_{(i,j) \in [1,p] \times B^c} S(i,j) = \sum_{j \in B^c} b_j = b(B^c).$$

If  $a(A) = b(B^c)$ ,  $S$  must be null on  $A^c \times B^c$ . If  $a(A) > b(B^c)$ , we get a contradiction, so  $\Gamma(X_0)$  is empty.

Actually, these causes of the non-existence of elements of  $\Gamma$  with support equal to or included in  $\text{Supp}(X_0)$  provide necessary and sufficient conditions. We give two criterions, the first one was already stated by Bacharach [1]. Pukelsheim gave a different formulation of the same statements in theorems 2 and 3 of [11]. We use a different method, relying on the theory of linear system of inequalities.

**Theorem 1.** (*Criteria to distinguish the cases*)

*The set  $\Gamma(X_0)$  is empty if and only if there exist two subsets  $A \subset [1, p]$  and  $B \subset [1, q]$  such that  $X_0$  is null on  $A \times B$  and  $a(A) > b(B^c)$ .*

*Assume now that  $\Gamma(X_0)$  is not empty. Then no matrix in  $\Gamma$  has the same support as  $X_0$  if and only if there exist two subsets  $A$  of  $[1, p]$  and  $B$  of  $[1, q]$  such that  $X_0$  is null on  $A \times B$  and  $a(A) = b(B^c)$ .*

Note that the assumption that  $X_0$  has at least a positive entry on each row or column prevents  $A$  and  $B$  from being full when  $X_0$  is null on  $A \times B$ . The additional condition  $a(A) > b(B^c)$  (respectively  $a(A) = b(B^c)$ ) is equivalent to the condition  $a(A) + b(B) > 1$  (respectively  $a(A) + b(B) = 1$ ), so rows and column play a symmetric role. These conditions and the positivity of all components of  $a$  and  $b$  also prevent  $A$  and  $B$  from being empty. We will call *cause of incompatibility* any (non-empty) block  $A \times B \subset [1, p] \times [1, q]$  such that  $X_0$  is null on  $A \times B$  and  $a(A) > b(B^c)$ .

We now describe the asymptotic behavior of sequence  $(X_n)_{n \geq 0}$  in each case. The first case is already well-known.

**Theorem 2.** (*Case of fast convergence*) *Assume that  $\Gamma$  contains some matrix with same support as  $X_0$ . Then*

1. *The sequences  $R_i(X_{2n})_{n \geq 0}$  and  $C_j(X_{2n+1})_{n \geq 0}$  converge to 1 at an at least geometric rate.*
2. *The sequence  $(X_n)_{n \geq 0}$  converges at an at least geometric rate to some matrix  $X_\infty$  which has the same support as  $X_0$ .*
3. *The limit  $X_\infty$  is the only matrix in  $\Gamma \cap \Delta_p X_0 \Delta_q$ . It is also the unique matrix achieving the minimum of  $D(Y||X_0)$  over all  $Y \in \Gamma(X_0)$ .*

For example, if  $p = q = 2$ ,  $a_1 = b_1 = 2/3$ ,  $a_2 = b_2 = 1/3$ , and

$$X_0 = \frac{1}{4} \begin{pmatrix} 2 & 1 \\ 1 & 0 \end{pmatrix}.$$

Then for every  $n \geq 1$ ,  $X_n$  or  $X_n^\top$  is equal to

$$\frac{1}{3(2^n - 1)} \begin{pmatrix} 2^n & 2^n - 2 \\ 2^n - 1 & 0 \end{pmatrix},$$

depending on whether  $n$  is odd or even. The limit is

$$X_\infty = \frac{1}{3} \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}.$$

The second case is also well-known, except the fact that the quantities  $R_i(X_{2n}) - 1$  and  $C_j(X_{2n+1}) - 1$  are  $o(n^{-1/2})$ .

**Theorem 3.** (*Case of slow convergence*) Assume that  $\Gamma$  contains some matrix with support included in  $\text{Supp}(X_0)$  but contains no matrix with support equal to  $\text{Supp}(X_0)$ . Then

1. The series

$$\sum_{n \geq 0} (R_i(X_{2n}) - 1)^2 \text{ and } \sum_{n \geq 0} (C_j(X_{2n+1}) - 1)^2$$

converge.

2. The sequences  $(\sqrt{n}(R_i(X_n) - 1))_{n \geq 0}$  and  $(\sqrt{n}(C_j(X_n) - 1))_{n \geq 0}$  converge to 0. In particular, the sequences  $(R_i(X_n))_{n \geq 0}$  and  $(C_j(X_n))_{n \geq 0}$  converge to 1.

3. The sequence  $(X_n)_{n \geq 0}$  converges to some matrix  $X_\infty$  whose support contains the support of every matrix in  $\Gamma(X_0)$ .

4. The limit  $X_\infty$  is the unique matrix achieving the minimum of  $D(Y||X_0)$  over all  $Y \in \Gamma(X_0)$ .

5. If  $(i, j) \in \text{Supp}(X_0) \setminus \text{Supp}(X_\infty)$ , the infinite product  $R_i(X_0)C_j(X_1)R_i(X_2)C_j(X_3) \cdots$  is infinite.

Actually the assumption that  $\Gamma$  contains no matrix with support equal to  $\text{Supp}(X_0)$  can be removed; but when this assumption fails, theorem 2 applies, so theorem 3 brings nothing new. When this assumption holds, the last conclusion of theorem 3 shows that the rate of convergence cannot be in  $o(n^{-1-\varepsilon})$  for any  $\varepsilon > 0$ .

However, a rate of convergence in  $\Theta(n^{-1})$  is possible, and we do not know whether other rates of slow convergence may occur. For example, consider  $p = q = 2$ ,  $a_1 = a_2 = b_1 = b_2 = 1/2$ , and

$$X_0 = \frac{1}{3} \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}.$$

Then for every  $n \geq 1$ ,  $X_n$  or  $X_n^\top$  is equal to

$$\frac{1}{2n+2} \begin{pmatrix} 1 & n \\ n+1 & 0 \end{pmatrix},$$

depending on whether  $n$  is odd or even. The limit is

$$X_\infty = \frac{1}{2} \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}.$$

When  $\Gamma$  contains no matrix with support included in  $\text{Supp}(X_0)$ , we already know by Gietl and Reffel's theorem [6] that both sequences  $(X_{2n})_{n \geq 0}$  and  $(X_{2n+1})_{n \geq 0}$  converge. The next two theorems improve on this result by giving a complete description of the two limit points and how to find them.

**Theorem 4.** (*Case of divergence*) Assume that  $\Gamma$  contains no matrix with support included in  $\text{Supp}(X_0)$ .

Then there exist some positive integer  $r \leq \min(p, q)$ , some partitions  $\{I_1, \dots, I_r\}$  of  $[1, p]$  and  $\{J_1, \dots, J_r\}$  of  $[1, q]$  such that:

1.  $(R_i(X_{2n})_{n \geq 0})$  converges to  $\lambda_k = b(J_k)/a(I_k)$  whenever  $i \in I_k$ ;
2.  $(C_j(X_{2n+1})_{n \geq 0})$  converges  $\lambda_k^{-1}$  whenever  $j \in J_k$ ;
3.  $X_n(i, j) = 0$  for every  $n \geq 0$  whenever  $i \in I_k$  and  $j \in J_{k'}$  with  $k < k'$ ;
4.  $X_n(i, j) \rightarrow 0$  as  $n \rightarrow +\infty$  at a geometric rate whenever  $i \in I_k$  and  $j \in J_{k'}$  with  $k > k'$ ;
5. The sequence  $(X_{2n})_{n \geq 0}$  converges to the unique matrix achieving the minimum of  $D(Y||X_0)$  over all  $Y \in \Gamma(a', b, X_0)$ , where  $a'_i/a_i = \lambda_k$  whenever  $i \in I_k$ ;
6. The sequence  $(X_{2n+1})_{n \geq 0}$  converges to the unique matrix achieving the minimum of  $D(Y||X_0)$  over all  $Y \in \Gamma(a, b', X_0)$ , where  $b'_j/b_j = \lambda_k^{-1}$  whenever  $j \in J_k$ ;
7. The support of any matrix in  $\Gamma(a', b, X_0) \cup \Gamma(a, b', X_0)$  is contained in  $I_1 \times J_1 \cup \dots \cup I_r \times J_r$ .
8. Let  $D_1 = \text{Diag}(a'_1/a_1, \dots, a'_p/a_p)$  and  $D_2 = \text{Diag}(b_1/b'_1, \dots, b_q/b'_q)$ . Then for every  $S \in \Gamma(a, b', X_0)$ ,  $D_1 S = S D_2 \in \Gamma(a', b, X_0)$ , and all matrices in  $\Gamma(a', b, X_0)$  can be written in this way.

For example, if  $p = q = 2$ ,  $a_1 = b_1 = 1/3$ ,  $a_2 = b_2 = 2/3$ , and

$$X_0 = \frac{1}{3} \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}.$$

Then for every  $n \geq 1$ ,  $X_n$  or  $X_n^\top$  is equal to

$$\frac{1}{3(3 \times 2^{n-1} - 1)} \begin{pmatrix} 1 & 3 \times 2^{n-1} - 2 \\ 2(3 \times 2^{n-1} - 1) & 0 \end{pmatrix},$$

depending on whether  $n$  is odd or even. The two limit points are

$$\frac{1}{3} \begin{pmatrix} 0 & 1 \\ 2 & 0 \end{pmatrix} \text{ and } \frac{1}{3} \begin{pmatrix} 0 & 2 \\ 1 & 0 \end{pmatrix},$$

so  $a'_1 = b'_1 = 2/3$  and  $a'_2 = b'_2 = 1/3$ .

The symmetry in theorem 4 shows that the limit points of  $(X_n)_{n \geq 0}$  would be the same if we would applying  $T_C$  first instead of  $T_R$ .

Actually, the assumption that  $\Gamma(X_0)$  is empty can be removed and it is not used in the proof of theorem 4. Indeed, when  $\Gamma(X_0)$  is non-empty, the conclusions still hold with  $r = 1$  and  $\lambda_1 = 1$ , but theorem 4 brings nothing new in this case.

Theorem 4 does not indicate what the partitions  $\{I_1, \dots, I_r\}$  and  $\{J_1, \dots, J_r\}$  are. Actually the integer  $r$ , the partitions  $\{I_1, \dots, I_r\}$  and  $\{J_1, \dots, J_r\}$  depend only on  $a$ ,  $b$  and on the support of  $X_0$ . and can be determined recursively as follows. This gives a complete description of the two limit points mentioned in theorem 4.

**Theorem 5.** (Determining the partitions in case of divergence) Keep the assumption and the notations of theorem 4. Fix  $k \in [1, r]$ , set  $P = [1, p] \setminus (I_1 \cup \dots \cup I_{k-1})$ ,  $Q = [1, q] \setminus (J_1 \cup \dots \cup J_{k-1})$ , and consider the restricted problem associated to the marginals  $a(\cdot|P) = (a_i/a(P))_{i \in P}$ ,  $b(\cdot|Q) = (b_j/b(Q))_{j \in Q}$  and to the initial condition  $(X_0(i, j))_{(i, j) \in P \times Q}$ .

If  $k = r$ , this restricted problem admits some solution.

If  $k < r$ , the set  $A_k \times B_k := I_k \times (Q \setminus J_k)$  is a cause of incompatibility of this restricted problem. More precisely, among all causes of incompatibility  $A \times B$  maximizing the ratio  $a(A)/b(B^c)$ , it is the one which maximizes the set  $A$  and minimizes the set  $B$ .

Note that if a cause of incompatibility  $A \times B$  maximizes the ratio  $a(A)/b(B^c)$ , then it is maximal for the inclusion order. We now give an example to illustrate how theorem 5 enables us to determine the partitions  $\{I_1, \dots, I_r\}$  and  $\{J_1, \dots, J_r\}$ . In the following array, the  $*$  and 0 indicate the positive and the null entries in  $X_0$ ; the last column and row indicate the target sums on each row and column.

*	*	0	0	0	0	.25
0	*	*	0	0	0	.25
0	*	*	*	0	0	.25
*	*	*	*	0	*	.15
*	0	*	*	*	*	.10
.05	.05	.1	.2	.2	.4	1

We indicate below in underlined boldface characters some blocks  $A \times B$  of zeroes which are causes of incompatibility, and the corresponding ratios  $a(A)/b(B^c)$ .

	*	*	0	0	<u>0</u>	0	.25
$A = \{1, 2, 3, 4\}$	0	*	*	0	<u>0</u>	0	.25
$B = \{5\}$	0	*	*	*	<u>0</u>	0	.25
$\frac{a(A)}{b(B^c)} = \frac{0.9}{0.8}$	*	*	*	*	<u>0</u>	*	.15
	*	0	*	*	*	*	.10
	.05	.05	.1	.2	.2	.4	1

	*	*	0	0	0	0	.25
$A = \{2, 3\}$	<u>0</u>	*	*	0	<u>0</u>	<u>0</u>	.25
$B = \{1, 5, 6\}$	<u>0</u>	*	*	*	<u>0</u>	<u>0</u>	.25
$\frac{a(A)}{b(B^c)} = \frac{0.5}{0.35}$	*	*	*	*	0	*	.15
	*	0	*	*	*	*	.10
	.05	.05	.1	.2	.2	.4	1

	*	*	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	.25
$A = \{1\}$	0	*	*	0	0	0	.25
$B = \{3, 4, 5, 6\}$	0	*	*	*	0	0	.25
$\frac{a(A)}{b(B^c)} = \frac{0.25}{0.1}$	*	*	*	*	0	*	.15
	*	0	*	*	*	*	.10
	.05	.05	.1	.2	.2	.4	1

	*	*	0	<u>0</u>	<u>0</u>	<u>0</u>	.25
$A = \{1, 2\}$	0	*	*	<u>0</u>	<u>0</u>	<u>0</u>	.25
$B = \{4, 5, 6\}$	0	*	*	*	0	0	.25
$\frac{a(A)}{b(B^c)} = \frac{0.5}{0.2}$	*	*	*	*	0	*	.15
	*	0	*	*	*	*	.10
	.05	.05	.1	.2	.2	.4	1

One checks that the last two blocks are those which maximize the ratio  $a(A)/b(B^c)$ . Among these two blocks, the latter has a bigger  $A$  and a smaller  $B$ , so it is  $A_1 \times B_1$ . Therefore,  $I_1 = \{1, 2\}$  and  $J_1 = \{1, 2, 3\}$ , and we look at the restricted problem associated to the marginals  $a(\cdot|I_1^c)$ ,  $b(\cdot|J_1^c)$  and to the initial condition  $(X_0(i, j))_{(i, j) \in I_1^c \times J_1^c}$ . The dots below indicate the removed rows and columns.

.	.	.	.	.	.	.		.
.	.	.	.	.	.	.		.
.	.	.	*	0	0	.		.5
.	.	.	*	0	*	.		.3
.	.	.	*	*	*	.		.2
.	.	.	.25	.25	.5	.		1

Two causes of impossibility have to be considered, namely  $\{3, 4\} \times \{5\}$  and  $\{3\} \times \{5, 6\}$ . The latter maximizes the ratio  $a(A)/b(J_1^c \setminus B)$ , so it is  $A_2 \times B_2$ . Therefore,  $I_2 = \{3\}$  and  $J_2 = \{4\}$ , and we look at the restricted problem below.

.	.	.	.	.	.	.		.
.	.	.	.	.	.	.		.
.	.	.	.	.	.	.		.
.	.	.	.	0	*	.		.6
.	.	.	.	*	*	.		.4
.	.	.	.	.33	.67	.		1

This time, there is no cause of impossibility, so  $r = 3$ , and the sets  $I_3 = \{4, 5\}$ ,  $J_3 = \{5, 6\}$  contain all the remaining indices. We shall indicate with dashlines the block structure defined by the partitions  $\{I_1, I_2, I_3\}$  and  $\{J_1, J_2, J_3\}$  (for readability, our example was chosen in such a way that each block is made of consecutive indices). By theorem 4, the limit of the sequence  $(X_{2n})_{n \geq 0}$  admits marginals  $a'$  and  $b$  and has support included in  $\text{Supp}(X_0)$ , namely it solves the problem below.

*	*	0	0	0	0	.		.1
0	*	*	0	0	0	.		.1
0	*	*	*	0	0	.		.2
*	*	*	*	0	*	.		.36
*	0	*	*	*	*	.		.24
.05	.05	.1	.2	.2	.4	.		1

In this example, no minimization of  $I$ -divergence is required to get the limit of  $(X_{2n})_{n \geq 0}$  since the set  $\Gamma(a', b, X_0)$  contains only one matrix, namely

.05	.05	0	0	0	0	.		.1
0	0	0.1	0	0	0	.		.1
0	0	0	.2	0	0	.		.2
0	0	0	0	0	.36	.		.36
0	0	0	0	.2	.04	.		.24
.05	.05	.1	.2	.2	.4	.		1

We note that the limit of  $X_{2n}(2, 2)$  is 0, but this convergence is slow since

$$\lim_{n \rightarrow +\infty} \frac{X_{2n+2}(2, 2)}{X_{2n}(2, 2)} = \lim_{n \rightarrow +\infty} \frac{1}{L_2(X_{2n})C_2(X_{2n+1})} = \frac{1}{\lambda_1 \lambda_1^{-1}} = 1.$$



Our approach to prove the convergence of the sequences  $(X_{2n})_{n \geq 0}$  and  $(X_{2n+1})_{n \geq 0}$  is completely different from Gietl and Reffel's method, which relies on  $I$ -divergence, although  $I$ -divergence helps us to determine the limit points. Our first step is to prove the convergence of the sequences  $(R_i(X_{2n}))_{n \geq 0}$  and  $(C_j(X_{2n+1}))_{n \geq 0}$  by exploiting recursions relations involving stochastic matrices. The proof relies on the next general result on infinite products of stochastic matrices.

**Theorem 6.** *Let  $(M_n)_{n \geq 1}$  be some sequence of  $d \times d$  stochastic matrices. Assume that there exists some constants  $\gamma > 0$ , and  $\rho \geq 1$  such that for every  $n \geq 1$  and  $i, j$  in  $[1, d]$ ,  $M_n(i, i) \geq \gamma$  and  $M_n(i, j) \leq \rho M_n(j, i)$ . Then the sequence  $(M_n \cdots M_1)_{n \geq 1}$  has a finite variation in the following sense: given any norm  $\|\cdot\|$  on the space of all  $d \times d$  real matrices, the series  $\sum_n \|M_{n+1} \cdots M_1 - M_n \cdots M_1\|$  converges. Thus the sequence  $(M_n \cdots M_1)_{n \geq 0}$  converges to some stochastic matrix  $L$ . Moreover, the series  $\sum_n M_n(i, j)$  and  $\sum_n M_n(j, i)$  converge whenever the rows of  $L$  with indexes  $i$  and  $j$  are different.*

An important literature deals with infinite products of stochastic matrices, with various motivations: study of inhomogeneous Markov chains, of opinion dynamics... See for example [13]. Backward infinite products converge much more often than forward infinite products. Many theorems involve the ergodic coefficients of stochastic matrices. For a  $d \times d$  stochastic matrix  $M$ , the ergodic coefficient is the quantity

$$\tau(M) = \min_{1 \leq i, i' \leq d} \sum_{j=1}^d \min(M(i, j), M(i', j)) \in [0, 1].$$

The difference  $1 - \tau(M)$  is the maximal total variation distance between the lines of  $M$  seen as probabilities on  $[1, d]$ . These theorems do not apply in our context.

To our knowledge, theorem 6 is new. The closest statements we found in the literature are Lorenz' stabilization theorem (theorem 2 of [9]) and a theorem of Touri and Nedić on infinite product of bistochastic matrices (theorem 7 of [14], relying on theorem 6 of [16]). The method we use to prove theorem 6 is different of theirs.

On the one hand, theorem 6 provides a stronger conclusion (namely finite variation and not only convergence) and has weaker assumptions than Lorenz' stabilization theorem. Indeed, Lorenz assumes that each  $M_n$  has a positive diagonal and a symmetric support, and that the entries of all matrices  $M_n$  are bounded below by some  $\delta > 0$ ; this entails the assumptions of our theorem 6, with  $\gamma = \delta$  and  $\rho = \delta^{-1}$ .

On the other hand, Lorenz' stabilization theorem gives more precisions on the limit  $L = \lim_{n \rightarrow +\infty} M_n \cdots M_1$ . In particular, if the support of  $M_n$  does not depends on  $n$ , then Lorenz shows that by applying a same permutation on the rows and on the columns of  $L$ , one gets a block-diagonal matrix in which each diagonal block is a consensus matrix, namely a stochastic matrix whose rows are all the same. This additional conclusion does not hold anymore under our weaker assumptions. For example, for every  $r \in [-1, 1]$ , consider the stochastic matrix

$$M(r) = \frac{1}{2} \begin{pmatrix} 1+r & 1-r \\ 1-r & 1+r \end{pmatrix}.$$

One checks that for every  $r_1$  and  $r_2$  in  $[-1, 1]$ ,  $M(r_2)M(r_1) = M(r_2 r_1)$ . Let  $(r_n)_{n \geq 1}$  be any sequence of numbers in  $]0, 1]$  whose infinite product converges to some  $\ell > 0$ . Then our assumptions hold with  $\gamma = 1/2$  and  $\rho = 1$  and the matrices  $M(r_n)$  have the same support. Yet, the limit of the products  $M(r_n) \cdots M(r_1)$ , namely  $M(\ell)$ , has only positive coefficients and is not a consensus matrix.

Note also that, given an arbitrary sequence  $(M_n)_{n \geq 1}$  of stochastic matrices, assuming only that the diagonal entries are bounded away from 0 does not ensure the convergence of the infinite product  $\cdots M_2 M_1$ . Indeed, consider the triangular stochastic matrices

$$T_0 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1/2 & 1/2 \end{pmatrix}, \quad T_1 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1/2 & 0 & 1/2 \end{pmatrix}.$$

A recursion shows that for every  $n \geq 1$  and  $(\varepsilon_1, \dots, \varepsilon_n) \in \{0, 1\}^n$ ,

$$T_{\varepsilon_n} \cdots T_{\varepsilon_1} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ r & 1 - 2^{-n} - r & 2^{-n} \end{pmatrix}, \quad \text{where } r = \sum_{k=1}^n \frac{\varepsilon_k}{2^{n+1-k}}.$$

Hence, one sees that the infinite product  $\cdots T_0 T_1 T_0 T_1 T_0 T_1$  diverges.

Yet, for a sequence of *doubly-stochastic* matrices, it is sufficient to assume that the diagonal entries are bounded away from 0. This result was proved by Touri and Nedić (theorem 5 of [15] or theorem 7 of [14], relying on theorem 6 of [16]). We provide a simpler proof and a slight improvement, showing that the sequence  $(M_n \cdots M_1)_{n \geq 1}$  not only converges but also has a finite variation.

**Theorem 7.** *Let  $(M_n)_{n \geq 1}$  be some sequence of  $d \times d$  doubly-stochastic matrices. Assume that there exists some constant  $\gamma > 0$  such that for every  $n \geq 1$  and  $i$  in  $[1, d]$ ,  $M_n(i, i) \geq \gamma$ . Then the sequence  $(M_n \cdots M_1)_{n \geq 1}$  has a finite variation. Thus the sequence  $(M_n \cdots M_1)_{n \geq 1}$  converges to some stochastic matrix  $L$ . Moreover, the series  $\sum_n M_n(i, j)$  and  $\sum_n M_n(j, i)$  converge whenever the rows of  $L$  with indexes  $i$  and  $j$  are different.*

Our proof relies on the following fact: define the *dispersion* of any column vector  $V \in \mathbf{R}^d$  by

$$D(V) = \sum_{1 \leq i, j \leq d} |V(i) - V(j)|.$$

Then, under the assumptions of theorem 7, the inequality

$$\gamma \|M_{n+1} \cdots M_1 V - M_n \cdots M_1 V\|_1 \leq D(M_n \cdots M_1 V) - D(M_{n+1} \cdots M_1 V).$$

holds for every  $n \geq 0$ .

### 3 Infinite products of stochastic matrices

#### 3.1 Proof of theorem 6

We begin with an elementary lemma.

**Lemma 8.** *Let  $M$  be any  $m \times n$  stochastic matrix and  $V \in \mathbf{R}^n$  be a column vector. Denote by  $\underline{M}$  the smallest entry of  $M$ , by  $\underline{V}$ ,  $\overline{V}$  and  $\text{diam}(V) = \overline{V} - \underline{V}$  the smallest entry, the largest entry and the diameter of  $V$ . Then*

$$\underline{MV} \geq (1 - \underline{M}) \underline{V} + \underline{M} \overline{V} \geq \underline{V},$$

$$\overline{MV} \leq \underline{M} \underline{V} + (1 - \underline{M}) \overline{V} \leq \overline{V},$$

so

$$\text{diam}(MV) \leq (1 - 2\underline{M}) \text{diam}(V).$$

*Proof.* Call  $M(i, j)$  the entries of  $M$  and  $V(1), \dots, V(n)$  the entries of  $V$ . Let  $j_1$  and  $j_2$  be indexes such that  $V(j_1) = \underline{V}$  and  $V(j_2) = \overline{V}$ . Then for every  $i \in [1, m]$ ,

$$\begin{aligned}
(MV)_i &= \sum_{j \neq j_2} M(i, j)V(j) + M(i, j_2)V(j_2) \\
&\geq \sum_{j \neq j_2} M(i, j)\underline{V} + M(i, j_2)\overline{V} \\
&= \underline{V} + M(i, j_2)(\overline{V} - \underline{V}) \\
&\geq \underline{V} + \underline{M}(\overline{V} - \underline{V}) \\
&\geq \underline{V}.
\end{aligned}$$

The first inequality follows. Applying it to  $-V$  yields the second inequality.  $\square$

The interesting case is when  $n \geq 2$ , so  $\underline{M} \leq 1/2$  and  $1 - 2\underline{M} \geq 0$ . Yet, the lemma and the proof above still apply when  $n = 1$ , since  $\overline{MV} = \underline{MV} = \overline{V} = \underline{V}$  in this case.

We now restrict ourselves to square stochastic matrices. To every column vector  $V \in \mathbf{R}^d$ , we associate the column vector  $V^\uparrow \in \mathbf{R}^d$  obtained by ordering the components in non-decreasing order. In particular  $V^\uparrow(1) = \underline{V}$  and  $V^\uparrow(d) = \overline{V}$ .

In the next lemmas and corollary, we establish inequalities that will play a key role in the proof of theorem 6.

**Lemma 9.** *Let  $M$  be some  $d \times d$  stochastic matrix with diagonal entries bounded below by some constant  $\gamma > 0$ , and  $V \in \mathbf{R}^d$  be a column vector with components in increasing order  $V(1) \leq \dots \leq V(d)$ . Let  $\sigma$  be a permutation of  $[1, d]$  such that  $(MV)(\sigma(1)) \leq \dots \leq (MV)(\sigma(d))$ . For every  $i \in [1, d]$ , set*

$$A_i = \sum_{j=1}^{i-1} M(\sigma(i), j) [V(i) - V(j)], \quad B_i = \sum_{j=i+1}^d M(\sigma(i), j) [V(j) - V(i)],$$

with the natural conventions  $A_1 = B_d = 0$ . The following statements hold.

1. For every  $i \in [1, d]$ ,  $(MV)^\uparrow(i) - V^\uparrow(i) = B_i - A_i$ .
2. All the terms in the sums defining  $A_i$  and  $B_i$  are non-negative.
3.  $B_i \geq M(\sigma(i), \sigma(i)) [V(\sigma(i)) - V(i)] \geq \gamma [V(\sigma(i)) - V(i)]$  whenever  $i < \sigma(i)$ .
4. Let  $a < b$  in  $[1, d]$ . If the orbit  $O(a)$  of  $a$  associated to the permutation  $\sigma$  contains some integer at least equal to  $b$ , then

$$V(b) - V(a) \leq \gamma^{-1} \sum_{i \in O(a) \cap [1, b-1]} B_i \mathbf{1}_{[i < \sigma(i)]} \leq \gamma^{-1} \sum_{i \in O(a) \cap [1, b-1]} B_i.$$

5. One has

$$\sum_{i=1}^d |V(\sigma(i)) - V(i)| \leq 2\gamma^{-1} \sum_{i=1}^d B_i \mathbf{1}_{[i < \sigma(i)]} \leq 2\gamma^{-1} \sum_{i=1}^{d-1} B_i.$$

*Proof.* By assumption,

$$(MV)^\uparrow(i) - V^\uparrow(i) = (MV)(\sigma(i)) - V(i) = \sum_{j=1}^d M(\sigma(i), j) [V(j) - V(i)] = -A_i + B_i,$$

which yields the first item. The next two items follow directly from the assumptions  $V(1) \leq \dots \leq V(d)$  and  $M(j, j) \geq \gamma$  for every  $j \in [1, d]$ .

Under the assumptions of item 4, the integer  $n(a, b) = \min\{n \geq 1 : \sigma^n(a) \geq b\}$  is well-defined and

$$\begin{aligned} V(b) - V(a) &\leq V(\sigma^{n(a,b)}(a)) - V(a) \\ &\leq \sum_{k=0}^{n(a,b)-1} [V(\sigma^{k+1}(a)) - V(\sigma^k(a))] \mathbf{1}_{\sigma^k(a) < \sigma^{k+1}(a)} \\ &\leq \gamma^{-1} \sum_{k=0}^{n(a,b)-1} B_{\sigma^k(a)} \mathbf{1}_{\sigma^k(a) < \sigma^{k+1}(a)} \end{aligned}$$

by item 3. Item 4 follows.

Since the sum of  $V(\sigma(i)) - V(i)$  over all  $i \in [1, d]$  is null and since  $V(1) \leq \dots \leq V(d)$ , one has

$$\sum_{i=1}^d |V(\sigma(i)) - V(i)| = 2 \sum_{i=1}^d (V(\sigma(i)) - V(i)) \mathbf{1}_{[i < \sigma(i)]} \leq 2\gamma^{-1} \sum_{i=1}^{d-1} B_i \mathbf{1}_{[i < \sigma(i)]},$$

by item 3. The proof is complete.  $\square$

We denote by  $\|\cdot\|_1$  the norm on  $\mathbf{R}^d$  defined as the sum of the absolute values of the components.

**Lemma 10.** *Keep the assumptions and the notations of lemma 9. Assume that there exists some constant  $\rho \geq 1$  such that for every  $n \geq 1$  and  $i, j$  in  $[1, d]$ ,  $M(i, j) \leq \rho M(j, i)$ . Set  $C = d(d-1) \max(\gamma^{-1}, \rho)$ . Then the following statements hold*

1. *For every  $i \in [1, d]$ ,  $A_i \leq (i-1) \max(\gamma^{-1}, \rho)(B_1 + \dots + B_{i-1})$ .*
2. *For every  $m \in [1, d]$ ,  $B_1 + \dots + B_m \leq (1 + C + \dots + C^{m-1}) \|(MV)^\uparrow - V^\uparrow\|_1$ .*

*Proof.* Given  $i \in [2, d]$  and  $j \in [1, i-1]$ , let us check that

$$A_{i,j} := M(\sigma(i), j) [V(i) - V(j)] \leq \max(\gamma^{-1}, \rho)(B_1 + \dots + B_{i-1}).$$

We distinguish two cases.

- If the orbit of some  $k \in [1, j]$  contains some integer at least equal to  $i$ , then inequality 4 applied with  $(a, b) = (k, i)$  yields

$$A_{i,j} \leq V(i) - V(j) \leq V(i) - V(k) \leq \gamma^{-1} \sum_{z \in O(k) \cap [1, i-1]} B_z.$$

- Otherwise, the orbit of every element of  $[1, j]$  is contained in  $[1, i - 1]$ , so the orbit of every element of  $[i, d]$  is contained in  $[j + 1, d]$ . In particular, the orbits  $O(\sigma(i)) = O(i)$  and  $O(j)$  are disjoint. Applying inequality 3 and inequality 4 of lemma 9, once with  $(a, b) = (\sigma(i), i)$ , once with  $(a, b) = (j, \sigma^{-1}(j))$  yields

$$\begin{aligned}
A_{i,j} &= M(\sigma(i), j) [V(i) - V(\sigma(i))] + M(\sigma(i), j) [V(\sigma(i)) - V(\sigma^{-1}(j))] \\
&\quad + M(\sigma(i), j) [V(\sigma^{-1}(j)) - V(j)] \\
&\leq \mathbf{1}_{\sigma(i) < i} [V(i) - V(\sigma(i))] + \mathbf{1}_{\sigma^{-1}(j) < \sigma(i)} \rho M(j, \sigma(i)) [V(\sigma(i)) - V(\sigma^{-1}(j))] \\
&\quad + \mathbf{1}_{j < \sigma^{-1}(j)} [V(\sigma^{-1}(j)) - V(j)] \\
&\leq \gamma^{-1} \sum_{z \in O(i) \cap [1, i-1]} B_z + \rho B_{\sigma^{-1}(j)} + \gamma^{-1} \sum_{z \in O(j) \cap [1, \sigma^{-1}(j)-1]} B_z \\
&\leq \max(\gamma^{-1}, \rho) \sum_{z \in [1, i-1]} B_z.
\end{aligned}$$

In both cases, we have got the inequality  $A_{i,j} \leq \max(\gamma^{-1}, \rho)(B_1 + \dots + B_{i-1})$ . Summing over all  $j \in [1, i - 1]$  yields item 1.

Let  $m \in [1, d]$ . Equality  $(MV)^\uparrow(i) - V^\uparrow(i) = B_i - A_i$  and item 1 yield

$$\begin{aligned}
\sum_{i=1}^m B_i &\leq \sum_{i=1}^m |(MV)^\uparrow(i) - V^\uparrow(i)| + \sum_{i=1}^m A_i \\
&\leq \|(MV)^\uparrow - V^\uparrow\|_1 + \sum_{i=1}^m (i-1) \max(\gamma^{-1}, \rho)(B_1 + \dots + B_{i-1}) \\
&\leq \|(MV)^\uparrow - V^\uparrow\|_1 + \sum_{i=1}^m (d-1) \max(\gamma^{-1}, \rho)(B_1 + \dots + B_{m-1}) \\
&\leq \|(MV)^\uparrow - V^\uparrow\|_1 + C \sum_{i=1}^{m-1} B_i
\end{aligned}$$

The particular case where  $m = 1$  yields  $B_1 \leq \|(MV)^\uparrow - V^\uparrow\|_1$ . Item 2 follows by induction.  $\square$

**Corollary 11.** *Let  $M$  be some  $d \times d$  stochastic matrix with diagonal entries bounded below by some  $\gamma > 0$ . Assume that there exists some constant  $\rho \geq 1$  such that for every  $n \geq 1$  and  $i, j$  in  $[1, d]$ ,  $M(i, j) \leq \rho M(j, i)$ . Set  $C = d(d-1) \max(\gamma^{-1}, \rho)$ . Then for any column  $V \in \mathbf{R}^d$  the following statements hold.*

1. Fix  $m \in [1, d]$  and  $r \geq 1 + (m-1) \max(\gamma^{-1}, \rho)$ .

$$\sum_{i=1}^m r^{-i} (MV)^\uparrow(i) \geq \sum_{i=1}^m r^{-i} V^\uparrow(i).$$

2.  $\|MV - V\|_1 \leq (2 + C + \dots + C^{d-2}) \|(MV)^\uparrow - V^\uparrow\|_1$ .

*Proof.* By applying a same permutation to the components of  $V$ , to the rows and to the columns of  $M$ , one may assume that  $V(1) \leq \dots \leq V(d)$ . Let  $\sigma$  be a permutation of  $[1, d]$  such that  $(MV)(\sigma(1)) \leq \dots \leq (MV)(\sigma(d))$ . Then lemmas 9 and 10 apply.

For every  $i \in [1, m]$ ,

$$(MV)^\uparrow(i) - V^\uparrow(i) = B_i - A_i \geq B_i - (m-1) \max(\gamma^{-1}, \rho)(B_1 + \dots + B_{i-1}).$$

Summing over  $i$  yields

$$\begin{aligned} \sum_{i=1}^m r^{-i}((MV)^\uparrow(i) - V^\uparrow(i)) &\geq \sum_{j=1}^m r^{-j} B_j - \sum_{i=2}^m \sum_{j=1}^{i-1} r^{-i} (m-1) \max(\gamma^{-1}, \rho) B_j \\ &= \sum_{j=1}^m \left( r^{-j} - (m-1) \max(\gamma^{-1}, \rho) \sum_{i=j+1}^m r^{-i} \right) B_j \\ &\geq \sum_{j=1}^m \left( r^{-j} - (m-1) \max(\gamma^{-1}, \rho) \frac{r^{-(j+1)}}{1-r^{-1}} \right) B_j \\ &= \sum_{j=1}^m \frac{r^{-j}}{r-1} [r-1 - (m-1) \max(\gamma^{-1}, \rho)] B_j \\ &\geq 0. \end{aligned}$$

Furthermore, for every  $i \in [1, d]$ ,

$$|(MV)(\sigma(i)) - V(\sigma(i))| - |(MV)(\sigma(i)) - V(i)| \leq |V(\sigma(i)) - V(i)|.$$

Summing over  $i$  and using the last statements of lemma 9 and corollary 10 yield

$$\begin{aligned} \|MV - V\|_1 - \|(MV)^\uparrow - V^\uparrow\|_1 &\leq \sum_{i=1}^d |V(\sigma(i)) - V(i)| \\ &\leq 2\gamma^{-1} \sum_{i=1}^{d-1} B_i \\ &\leq (1 + C + \dots + C^{d-2}) \|(MV)^\uparrow - V^\uparrow\|_1 \end{aligned}$$

The proof is complete.  $\square$

We now derive the last step of the proof of theorem 6. Indeed, applying the next corollary to each vector of the canonical basis on  $\mathbf{R}^d$  yields theorem 6.

**Corollary 12.** *Let  $(M_n)_{n \geq 1}$  be some sequence of  $d \times d$  stochastic matrices. Assume that there exists some constants  $\gamma > 0$ , and  $\rho \geq 1$  such that for every  $n \geq 1$  and  $i, j$  in  $[1, d]$ ,  $M_n(i, i) \geq \gamma$  and  $M_n(i, j) \leq \rho M_n(j, i)$ . For every column vector  $V \in \mathbf{R}^d$ , the sequence of vectors  $(V_n)_{n \geq 0} := (M_n \dots M_1 V)_{n \geq 0}$  has a finite variation, so it converges. Moreover, the series  $\sum_n M_n(i, j)$  and  $\sum_n M_n(j, i)$  converge whenever the two sequences  $(V_n(i))_{n \geq 0}$  and  $(V_n(j))_{n \geq 0}$  have a different limit.*

*Proof.* Fix  $r \geq 1 + (d-1) \max(\gamma^{-1}, \rho)$ . For each  $n$ , one can apply corollary 11 to the matrix  $M_{n+1}$  and to the vector  $V_n$ .

For every  $m \in [1, d]$ , the sequence  $(r^{-1}V_n^\uparrow(1) + \dots + r^{-m}V_n^\uparrow(m))_{n \geq 0}$  is non-decreasing by corollary 11 (first part) and bounded above by  $r^{-1}V^\uparrow(d) + \dots + r^{-m}V^\uparrow(d)$ , thanks to lemma 8, so it has a finite variation and converges. By difference, each sequence  $(V_n^\uparrow(i))_{n \geq 0}$  has a finite variation. The convergence of the series  $\sum_n \|V_{n+1}^\uparrow - V_n^\uparrow\|_1$  follows, and also  $\sum_n \|V_{n+1} - V_n\|_1$  by corollary 11 (second part).

Call  $\lambda_1 < \dots < \lambda_r$  the distinct values of  $\lim_{n \rightarrow \infty} V_n(i)$  for  $i \in [1, d]$ . For every  $k \in [1, r]$ , set  $I_k = \{i \in [1, d] : \lim_{n \rightarrow \infty} V_n(i) = \lambda_k\}$ ,  $J_k = I_1 \cup \dots \cup I_k$  and call  $m_k$  the size of  $J_k$ . Fix  $\varepsilon > 0$  such that  $2\varepsilon < \gamma \min(\lambda_2 - \lambda_1, \dots, \lambda_r - \lambda_{r-1})$ , so that the intervals  $[\lambda_k - \varepsilon, \lambda_k + \varepsilon]$  are pairwise disjoint. Then one can find some non-negative integer  $N$ , such that  $V_n(i) \in [\lambda_k - \varepsilon, \lambda_k + \varepsilon]$  for every  $n \geq N$ ,  $k \in [1, r]$ , and  $i \in I_k$ .

Given  $k \in [1, r-1]$  and  $n \geq N$ , we show below that

$$\sum_{i=1}^{m_k} r^{-i} [V_{n+1}^\uparrow(i) - V_n^\uparrow(i)] \geq (\lambda_{k+1} - \lambda_k - 2\varepsilon) r^{-m_k} \sum_{i \in J_k} \sum_{j \in J_k^c} M_{n+1}(i, j).$$

Thus, the sequence  $(V_n^\uparrow)_{n \geq 0}$  and the inequalities  $M_n(j, i) \leq \rho M_n(i, j)$  will yield the convergence of the series  $\sum_n M_n(i, j)$  and  $\sum_n M_n(j, i)$  for every  $(i, j) \in J_k \times J_k^c$ .

Fix  $n \geq N$  and a permutation  $\sigma$  of  $[1, d]$  such that  $V_{n+1}(\sigma(1)) \leq \dots \leq V_{n+1}(\sigma(d))$ . Note that  $\sigma([1, m_k]) = J_k$ .

By construction, the column vector  $U_n$  defined by  $U_n(j) = \min(V_n(j), \lambda_k + \varepsilon)$  has the same  $m_k$  least components as  $V_n$  (corresponding to the indexes  $j \in J_k$ ), so  $U_n^\uparrow$  have the same  $m_k$  first components as  $V_n^\uparrow$ . Furthermore,  $V_n(j) - U_n(j) \geq \lambda_{k+1} - \lambda_k - 2\varepsilon$  for every  $j \in J_k^c$ .

Hence, for every  $i \in [1, d]$ ,

$$\begin{aligned} V_{n+1}^\uparrow(i) - (M_{n+1}U_n)(\sigma(i)) &= V_{n+1}(\sigma(i)) - (M_{n+1}U_n)(\sigma(i)) \\ &= (M_{n+1}V_n - M_{n+1}U_n)(\sigma(i)) \\ &= \sum_{j=1}^d M_{n+1}(\sigma(i), j) (V_n(j) - U_n(j)) \\ &\geq (\lambda_{k+1} - \lambda_k - 2\varepsilon) \sum_{j \in J_k^c} M_{n+1}(\sigma(i), j). \end{aligned}$$

Fix  $r \geq 1 + (m_k - 1) \max(\gamma^{-1}, \rho)$ . Then

$$\begin{aligned} \sum_{i=1}^{m_k} r^{-i} (V_{n+1}^\uparrow(i) - (M_{n+1}U_n)(\sigma(i))) &\geq (\lambda_{k+1} - \lambda_k - 2\varepsilon) \sum_{i=1}^{m_k} r^{-i} \sum_{j \in J_k^c} M_{n+1}(\sigma(i), j) \\ &\geq (\lambda_{k+1} - \lambda_k - 2\varepsilon) r^{-m_k} \sum_{i=1}^{m_k} \sum_{j \in J_k^c} M_{n+1}(\sigma(i), j) \\ &= (\lambda_{k+1} - \lambda_k - 2\varepsilon) r^{-m_k} \sum_{i \in J_k} \sum_{j \in J_k^c} M_{n+1}(i, j). \end{aligned}$$

But the rearrangement inequality and lemma 1 yield

$$\begin{aligned} \sum_{i=1}^{m_k} r^{-i} (M_{n+1}U_n)(\sigma(i)) &\geq \sum_{i=1}^{m_k} r^{-i} (M_{n+1}U_n)^\uparrow(i) \\ &\geq \sum_{i=1}^{m_k} r^{-i} U_n^\uparrow(i) \\ &= \sum_{i=1}^{m_k} r^{-i} V_n^\uparrow(i). \end{aligned}$$

We get the desired inequality by additioning the last two inequalities.

The proof is complete.  $\square$

### 3.2 Proof of theorem 7

The proof we give is simpler than the proof of theorem 6, although some arguments are very similar. We begin with the key lemma.

**Lemma 13.** *Let  $M$  be some  $d \times d$  doubly-stochastic matrix with diagonal entries bounded below by some constant  $\gamma > 0$ , and  $V \in \mathbf{R}^d$  be any column vector. Call dispersion of  $V$  the quantity*

$$D(V) = \sum_{1 \leq i, j \leq d} |V(i) - V(j)|.$$

*Then  $D(V) - D(MV) \geq \gamma \|MV - V\|_1$ .*

*Proof.* On the one hand, for every  $i$  and  $j$  in  $[1, d]$ ,

$$\begin{aligned} (MV)(i) - (MV)(j) &= \sum_{1 \leq k \leq d} M(i, k)V(k) - \sum_{1 \leq l \leq d} M(j, l)V(l) \\ &= \sum_{1 \leq k, l \leq d} M(i, k)M(j, l)(V(k) - V(l)), \end{aligned}$$

so

$$D(MV) = \sum_{1 \leq i, j \leq d} \left| \sum_{1 \leq k, l \leq d} M(i, k)M(j, l)(V(k) - V(l)) \right|.$$

On the other hand

$$\begin{aligned} D(V) &= \sum_{1 \leq k, l \leq d} |V(k) - V(l)| \\ &= \sum_{1 \leq i, j \leq d} \sum_{1 \leq k, l \leq d} M(i, k)M(j, l)|V(k) - V(l)|. \end{aligned}$$

By difference,  $D(V) - D(MV)$  is the sum over all  $i$  and  $j$  in  $[1, d]$  of the non negative quantities

$$\Delta(i, j) = \sum_{1 \leq k, l \leq d} M(i, k)M(j, l)|V(k) - V(l)| - \left| \sum_{1 \leq k, l \leq d} M(i, k)M(j, l)(V(k) - V(l)) \right|.$$

Thus

$$D(V) - D(MV) \geq \sum_{1 \leq i \leq d} \Delta(i, i).$$

But for every  $i \in [1, d]$ ,

$$\begin{aligned} \Delta(i, i) &= \sum_{1 \leq k, l \leq d} M(i, k)M(i, l)|V(k) - V(l)| - 0 \\ &\geq \sum_{1 \leq k \leq d} M(i, k)M(i, i)|V(k) - V(i)| \\ &\geq \gamma \sum_{1 \leq k \leq d} M(i, k)|V(k) - V(i)| \\ &\geq \gamma \left| \sum_{1 \leq k \leq d} M(i, k)(V(k) - V(i)) \right| \\ &= \gamma |(MV)(i) - V(i)|. \end{aligned}$$

The result follows. □



We now derive the last step of the proof of theorem 7. Indeed, applying the next corollary to each vector of the canonical basis on  $\mathbf{R}^d$  yields theorem 7.

**Corollary 14.** *Let  $(M_n)_{n \geq 1}$  be any sequence of  $d \times d$  bistochastic matrices with diagonal entries bounded below by some  $\gamma > 0$ . For every column vector  $V \in \mathbf{R}^d$ , the sequence  $(V_n)_{n \geq 0} := (M_n \dots M_1 V)_{n \geq 0}$  has a finite variation, so it converges. Moreover, the series  $\sum_n M_n(i, j)$  and  $\sum_n M_n(j, i)$  converge whenever the two sequences  $(V_n(i))_{n \geq 0}$  and  $(V_n(j))_{n \geq 0}$  have a different limit.*

*Proof.* Lemma 13 yields  $\gamma \|V_{n+1} - V_n\|_1 \leq D(V_n) - D(V_{n+1})$  for every  $n \geq 0$ . In particular, the sequence  $((D(V_n))_{n \geq 0})$  is non-increasing and bounded below by 0, so it converges. The convergence of the series  $\sum_n \|V_{n+1} - V_n\|_1$  and the convergence of the sequence  $(V_n)_{n \geq 0}$  follow.

Call  $\lambda_1 < \dots < \lambda_r$  the distinct values of  $\lim_{n \rightarrow \infty} V_n(i)$  for  $i \in [1, d]$ . For every  $k \in [1, r]$ , set  $I_k = \{i \in [1, d] : \lim_{n \rightarrow \infty} V_n(i) = \lambda_k\}$ , and  $J_k = I_1 \cup \dots \cup I_k$ .

The proof of the convergence of the series  $\sum_n M_{n+1}(i, j)$  for every  $(i, j) \in J_k \times J_k^c$  works like the proof of corollary 12, with  $r$  replaced by 1, thanks to lemma 15 stated below, so the rearrangement inequality becomes an equality.

Using the equality

$$\sum_{(i,j) \in J_k^c \times J_k} M_{n+1}(i, j) = |J_k| - \sum_{(i,j) \in J_k \times J_k} M_{n+1}(i, j) = \sum_{(i,j) \in J_k \times J_k^c} M_{n+1}(i, j),$$

we derive the convergence of the series  $\sum_n M_{n+1}(i, j)$  for every  $(i, j) \in J_k^c \times J_k$ . The proof is complete.  $\square$

**Lemma 15.** *Let  $M$  be some  $d \times d$  doubly-stochastic matrix. Then for every column vector  $V \in \mathbf{R}^d$  and  $m \in [1, d]$*

$$\sum_{i=1}^m (MV)^\uparrow(i) \geq \sum_{i=1}^m V^\uparrow(i).$$

*Proof.* By applying a same permutation to the columns of  $M$  and to the components of  $V$ , one may assume that  $V(1) \leq \dots \leq V(d)$ . By applying a permutation to the rows of  $M$ , one may assume also that  $(MV)(1) \leq \dots \leq (MV)(d)$ . Since  $M$  is doubly-stochastic, the real numbers

$$S(j) = \sum_{i=1}^m M(i, j) \text{ for } j \in [1, d]$$

are in  $[0, 1]$  and add up to  $m$ . Moreover

$$\sum_{i=1}^m (MV)(i) = \sum_{j=1}^d S(j)V(j).$$

Hence

$$\begin{aligned} \sum_{i=1}^m (MV)(i) - \sum_{j=1}^m V(j) &= \sum_{j=m+1}^d S(j)V(j) + \sum_{j=1}^m (S(j) - 1)V(j) \\ &\geq \sum_{j=m+1}^d S(j)V(m) + \sum_{j=1}^m (S(j) - 1)V(m) \\ &= 0. \end{aligned}$$

We are done.  $\square$

## 4 Proof of theorem 1

### 4.1 Condition for the non-existence of a solution with support included in $\text{Supp}(X_0)$

We assume that  $\Gamma$  contains no matrix with support included in  $\text{Supp}(X_0)$ , namely that the system

$$\begin{cases} \forall i \in [1, p], X(i, +) = a_i \\ \forall j \in [1, q], X(+, j) = b_j \\ \forall (i, j) \in [1, p] \times [1, q], X(i, j) \geq 0 \\ \forall (i, j) \in \text{Supp}(X_0)^c, X(i, j) = 0 \end{cases}$$

is inconsistent.

This system can be seen as a system of linear inequalities of the form  $\ell(X) \leq c$  (where  $\ell$  is some linear form and  $c$  some constant) by splitting each equality  $\ell(X) = c$  into the two inequalities  $\ell(X) \leq c$  and  $\ell(X) \geq c$ , and by transforming each inequality  $\ell(X) \geq c$  into the equivalent inequality  $-\ell(X) \leq -c$ . But theorem 4.2.3 in [17] (a consequence of Farkas' or Fourier's lemma) states that a system of linear inequalities of the form  $\ell(X) \leq c$  is inconsistent if and only if some linear combination with non-negative weights of the linear inequalities yields the inequality  $0 \leq -1$ .

Consider such a linear combination and call  $\alpha_{i,+}$ ,  $\alpha_{i,-}$ ,  $\beta_{j,+}$ ,  $\beta_{j,-}$ ,  $\gamma_{i,j,+}$ ,  $\gamma_{i,j,-}$  the weights associated to the inequalities  $X(i, +) \leq a_i$ ,  $-X(i, +) \leq -a_i$ ,  $X(+, j) \leq b_j$ ,  $-X(+, j) \leq -b_j$ ,  $X(i, j) \leq 0$ ,  $-X(i, j) \leq 0$ . When  $(i, j) \in \text{Supp}(X_0)$ , the inequality  $X(i, j) \leq 0$  does not appear in the system, so we set  $\gamma_{i,j,+} = 0$ . Then the real numbers  $\alpha_i := \alpha_{i,+} - \alpha_{i,-}$ ,  $\beta_j := \beta_{j,+} - \beta_{j,-}$ ,  $\gamma_{i,j} := \gamma_{i,j,+} - \gamma_{i,j,-}$  satisfy the following conditions:

- for every  $(i, j) \in [1, p] \times [1, q]$ ,  $\alpha_i + \beta_j + \gamma_{i,j} = 0$ ,
- $\gamma_{i,j} \leq 0$  whenever  $(i, j) \in \text{Supp}(X_0)$ ,
- $\sum_{i=1}^p \alpha_i a_i + \sum_{j=1}^q \beta_j b_j = -1$ .

Let  $U$  and  $V$  be two random variables with respective laws

$$\sum_{i=1}^p a_i \delta_{\alpha_i} \text{ and } \sum_{j=1}^q b_j \delta_{-\beta_j}.$$

Then

$$\int_{\mathbf{R}} (P[U > t] - P[V > t]) dt = \mathbf{E}[U] - \mathbf{E}[V] = \sum_{i=1}^p \alpha_i a_i + \sum_{j=1}^q \beta_j b_j = -1 < 0,$$

so there exists some real number  $t$  such that  $P[U > t] - P[V > t] < 0$ . Consider the sets  $A = \{i \in [1, p] : \alpha_i \leq t\}$  and  $B = \{j \in [1, q] : \beta_j < -t\}$ . Then for every  $(i, j) \in A \times B$ ,  $\alpha_i + \beta_j < 0$ , so  $(i, j) \notin \text{Supp}(X_0)$ . Moreover,

$$a(A) - b(B^c) = \sum_{i \in A} a_i + \sum_{j \in B^c} b_j = P[U \leq t] + P[-V \geq -t] > 0.$$

The proof is complete.

## 4.2 Condition for the existence of additional zeroes shared by every solution in $\Gamma(X_0)$

We now assume that  $\Gamma$  contains some matrix with support included in  $\text{Supp}(X_0)$ , but no matrix with support equal to  $\text{Supp}(X_0)$ . By remark 23 (at the end of section 5), there exists a position  $(i_0, j_0) \in \text{Supp}(X_0)$  such that the entry  $S(i_0, j_0)$  of every  $S \in \Gamma$  is 0. Hence for every  $p \times q$  matrix  $X$  with real entries,

$$\left. \begin{array}{l} \forall i \in [1, p], \quad X(i, +) = a_i \\ \forall j \in [1, q], \quad X(+, j) = b_j \\ \forall (i, j) \in [1, p] \times [1, q], \quad X(i, j) \geq 0 \\ \forall (i, j) \in \text{Supp}(X_0)^c, \quad X(i, j) = 0 \end{array} \right\} \implies X(i_0, j_0) \leq 0.$$

and the system in the left-hand side of the implication is consistent. As before, the system at the left-hand side of the implication can be seen as a system of linear inequalities of the form  $\ell(X) \leq c$ .

We now use theorem 4.2.7 in [17] (a consequence of Farkas' or Fourier's lemma) which states that any linear inequation which is a consequence of some consistent system of linear inequalities of the form  $\ell(X) \leq c$  can be deduced from the system by legal linear combinations: multiplying inequalities by non-negative numbers, adding inequalities, adding the inequality  $0 \leq 1$ . Here, the inequality  $0 \leq 1$  cannot be involved since when the left-hand side of the implication holds, the inequality  $X(i_0, j_0) \leq 0$  is actually an equality.

As in subsection 4.1, we get real numbers  $(\alpha_i)_{1 \leq i \leq p}$ ,  $(\beta_j)_{1 \leq j \leq q}$  and  $(\gamma_{i,j})_{1 \leq i \leq p, 1 \leq j \leq q}$  such that

- for every  $(i, j) \in [1, p] \times [1, q]$ ,  $\alpha_i + \beta_j + \gamma_{i,j} = \delta_{i,i_0} \delta_{j,j_0}$ ,
- $\gamma_{i,j} \leq 0$  whenever  $(i, j) \in \text{Supp}(X_0)$ ,
- $\sum_{i=1}^p \alpha_i a_i + \sum_{j=1}^q \beta_j b_j = 0$ .

Let  $U$  and  $V$  be two random variables with respective laws

$$\sum_{i=1}^p a_i \delta_{\alpha_i} \text{ and } \sum_{j=1}^q b_j \delta_{-\beta_j}.$$

Then

$$\int_{\mathbf{R}} (P[U > t] - P[V > t]) dt = \mathbf{E}[U] - \mathbf{E}[V] = \sum_{i=1}^p \alpha_i a_i + \sum_{j=1}^q \beta_j b_j = 0,$$

so there exists some real number  $t$  such that  $P[U > t] - P[V > t] \leq 0$ . Consider the sets  $A = \{i \in [1, p] : \alpha_i \leq t\}$  and  $B = \{j \in [1, q] : \beta_j < -t\}$ . Then for every  $(i, j) \in A \times B$ ,  $\alpha_i + \beta_j < 0$ , so  $(i, j) \notin \text{Supp}(X_0)$ . Moreover,

$$a(A) - b(B^c) = \sum_{i \in A} a_i + \sum_{j \in B^c} b_j = P[U \leq t] + P[-V \geq -t] \geq 0.$$

and this inequality is necessarily an equality, since otherwise  $\Gamma$  would not contain any matrix with support included in  $\text{Supp}(X_0)$ . The proof is complete.

## 5 Tools and preliminary results

### 5.1 Results on the quantities $R_i(X_{2n})$ and $C_j(X_{2n+1})$

**Lemma 16.** *Let  $X \in \Gamma_1$ . Then*

$$\sum_{i=1}^q a_i R_i(X) = \sum_{i,j} X(i,j) = \sum_j b_j = 1$$

and for every  $j \in [1, q]$ ,

$$C_j(T_R(X)) = \sum_{i=1}^p \frac{X(i,j)}{b_j} R_i(X)^{-1}.$$

When  $X \in \Gamma_C$ , this equality expresses  $C_j(T_R(X))$  as a weighted (arithmetic) mean of the quantities  $R_i(X)^{-1}$ , with weights  $X(i,j)/b_j$ .

For every  $X \in \Gamma_1$ , call  $R(X)$  the column vecteur with components  $R_1(X), \dots, R_p(X)$  and  $C(X)$  the column vecteur with components  $C_1(X), \dots, C_q(X)$ . Set

$$\underline{R}(X) = \min_i R_i(X), \quad \overline{R}(X) = \max_i R_i(X), \quad \underline{C}(X) = \min_j C_j(X), \quad \overline{C}(X) = \max_j C_j(X).$$

**Corollary 17.** *The intervals*

$$[\overline{C}(X_1)^{-1}, \underline{C}(X_1)^{-1}], [\underline{R}(X_2), \overline{R}(X_2)], [\overline{C}(X_3)^{-1}, \underline{C}(X_3)^{-1}], [\underline{R}(X_4), \overline{R}(X_4)], \dots$$

contain 1 and form a non-increasing sequence.

In lemma 16, one can invert the roles of the lines and the columns. Given  $X \in \Gamma_C$ , the matrix  $T_R(X)$  is in  $\Gamma_R$  so the quantities  $R_i(T_C(T_R(X)))$  can be written as weighted (arithmetic) means of the  $C_j(T_R(X))^{-1}$ . But the  $C_j(T_R(X))$  can be written as a weighted (arithmetic) means of the quantities  $R_k(X)^{-1}$ . Putting things together, one gets weighted arithmetic means of weighted harmonic means. Next lemma shows how to transform these into weighted arithmetic means by modifying the weights.

**Lemma 18.** *Let  $X \in \Gamma_C$ . Then  $R(T_C(T_R(X))) = P(X)R(X)$ , where  $P(X)$  is the  $p \times p$  matrix given by*

$$P(X)(i, k) = \sum_{j=1}^q \frac{T_R(X)(i, j) T_R(X)(k, j)}{a_i b_j C_j(T_R(X))}.$$

The matrix  $P(X)$  is stochastic. Moreover it satisfies for every  $i$  and  $k$  in  $[1, p]$ ,

$$P(X)(i, i) \geq \frac{\underline{a}}{\overline{b} \overline{C}(T_R(X))_q}$$

and

$$P(X)(k, i) \leq \frac{\overline{a}}{\underline{a}} P(X)(i, k).$$

*Proof.* For every  $i \in [1, p]$ ,

$$R_i(T_C(T_R(X))) = \sum_{j=1}^q \frac{T_R(X)(i, j)}{a_i} \frac{1}{C_j(T_R(X))}.$$

But the assumption  $X \in \Gamma_C$  yields

$$1 = \frac{1}{b_j} \sum_{k=1}^p X(k, j) = \frac{1}{b_j} \sum_{k=1}^p T_R(X)(k, j) R_k(X).$$

Hence,

$$R_i(T_C(T_R(X))) = \sum_{j=1}^q \frac{T_R(X)(i, j)}{a_i} \sum_{k=1}^p \frac{T_R(X)(k, j)}{b_j C_j(T_R(X))} R_k(X).$$

These equalities can be written as  $R(T_C(T_R(X))) = P(X)R(X)$ , where  $P(X)$  is the  $p \times p$  matrix whose entries are given in the statement of lemma 18. By construction, the entries of  $P(X)$  are non-negative and for every  $i \in [1, p]$ ,

$$\sum_{k=1}^p P(X)(i, k) = \sum_{j=1}^q \frac{T_R(X)(i, j)}{a_i b_j C_j(T_R(X))} \sum_{k=1}^p T_R(X)(k, j) = \sum_{j=1}^q \frac{T_R(X)(i, j)}{a_i} = 1.$$

Moreover, since

$$\sum_{j=1}^q T_R(X)(i, j)^2 \geq \frac{1}{q} \left( \sum_{j=1}^q T_R(X)(i, j) \right)^2 = \frac{a_i^2}{q}$$

we have

$$\begin{aligned} P(X)(i, i) &\geq \frac{1}{a_i \bar{b} \bar{C}(T_R(X))} \sum_{j=1}^q T_R(X)(i, j)^2 \\ &= \frac{a_i}{\bar{b} \bar{C}(T_R(X)) q} \\ &\geq \frac{\underline{a}}{\bar{b} \bar{C}(T_R(X)) q}. \end{aligned}$$

The last inequality to be proved follows directly from the symmetry of the matrix  $(a_i P(X)(i, k))_{1 \leq i, k \leq p}$ .  $\square$

## 5.2 A function associated to each element of $\Gamma_1$

**Definition 19.** For every  $X$  and  $S$  in  $\Gamma_1$ , we set

$$F_S(X) = \prod_{(i, j) \in [1, p] \times [1, q]} X(i, j)^{S(i, j)},$$

with the convention  $0^0 = 1$ .

We note that  $0 \leq F_S(X) \leq 1$ , and that  $F_S(X) > 0$  if and only if  $\text{Supp}(S) \subset \text{Supp}(X)$ .

**Lemma 20.** Let  $S \in \Gamma_1$ . For every  $X \in \Gamma_1$ ,  $F_S(X) \leq F_S(S)$ , with equality if and only if  $X = S$ . Moreover, if  $\text{Supp}(S) \subset \text{Supp}(X)$ , then  $D(S||X) = \log_2(F_S(S)/F_S(X))$ .

*Proof.* Assume that  $\text{Supp}(S) \subset \text{Supp}(X)$ . The definition of  $F_S$  and the arithmetic-geometric inequality yield

$$\frac{F_S(S)}{F_S(X)} = \prod_{i, j} \left( \frac{X(i, j)}{S(i, j)} \right)^{S(i, j)} \leq \sum_{i, j} S(i, j) \left( \frac{X(i, j)}{S(i, j)} \right) = \sum_{i, j} X(i, j) = 1,$$

with equality if and only if  $X(i, j) = S(i, j)$  for every  $(i, j) \in \text{Supp}(S)$ . The result follows.  $\square$

**Lemma 21.** *Let  $x \in \Gamma_1$ .*

- *For every  $S \in \Gamma_R$  such that  $\text{Supp}(S) \subset \text{Supp}(X)$ , one has  $F_S(X) \leq F_S(T_R(X))$ , and the ratio  $F_S(X)/F_S(T_R(X))$  does not depend on  $S$ .*
- *For every  $S \in \Gamma_C$  such that  $\text{Supp}(S) \subset \text{Supp}(X)$ , one has  $F_S(X) \leq F_S(T_C(X))$ , and the ratio  $F_S(X)/F_S(T_C(X))$  does not depend on  $S$ .*

*Proof.* Let  $S \in \Gamma_R$ . For every  $(i, j) \in \text{Supp}(X)$ ,  $X(i, j)/(T_R(X))(i, j) = R_i(X)$  so the arithmetic-geometric mean inequality yields

$$\frac{F_S(X)}{F_S(T_R(X))} = \prod_{i,j} R_i(X)^{S_{i,j}} = \prod_i R_i(X)^{a_i} \leq \sum_i a_i R_i(X) = \sum_{i,j} X(i, j) = 1.$$

The first statement follows. The second statement is proved in the same way.  $\square$

**Corollary 22.** *Assume that  $\Gamma(X_0)$  is not empty. Then:*

1. *for every  $S \in \Gamma(X_0)$ , the sequence  $(F_S(X_n))_{n \geq 1}$  is non-decreasing and bounded above, so it converges ;*
2. *for every  $(i, j)$  in the union of the supports  $\text{Supp}(S)$  over all  $S \in \Gamma(X_0)$ , the sequence  $(X_n(i, j))_{n \geq 1}$  is bounded away from 0.*

*Proof.* Lemmas 20 and 21 yield the first item. Given  $S \in \Gamma(X_0)$  and  $(i, j) \in \text{Supp}(S)$ , we get for every  $n \geq 0$ ,  $X_n(i, j)^{S(i,j)} \geq F_S(X_n) \geq F_S(X_0) > 0$ . The second item follows.  $\square$

The first item of corollary 22 will yield the first items of theorem 3. The second item of corollary 22 is crucial to establish the geometric rate of convergence in theorem 2 and the convergence in theorem 3.

**Remark 23.** *Using the convexity of  $\Gamma(X_0)$ , we see that if  $\Gamma(X_0)$  is non-empty, one can construct a matrix  $S_0 \in \Gamma(X_0)$  whose support contains the support of every matrix in  $\Gamma(X_0)$ .*

## 6 Proof of theorem 2

In this section, we assume that  $\Gamma$  contains some matrix having the same support as  $X_0$ , and we establish the convergences with at least geometric rate stated in theorem 2. The main tools are lemma 8 and the second item of corollary 22. Corollary 22 shows that the non-zero entries of all matrices  $X_n$  are bounded below by some positive real number  $\gamma$ . Therefore, the non-zero entries of all matrices  $X_n X_n^\top$  are bounded below by  $\gamma^2$ . These matrix have the same support as  $X_0 X_0^\top$ .

By lemma 18, for every  $n \geq 1$ ,  $R(X_{2n+2}) = P(X_{2n})R(X_{2n})$ , where  $P(X_{2n})$  is a stochastic matrix given by

$$P(X_{2n})(i, i') = \sum_{j=1}^q \frac{X_{2n+1}(i, j)X_{2n+1}(i', j)}{a_i b_j C_j(X_{2n+1})}.$$

These matrices have also the same support as  $X_0 X_0^\top$ . Moreover, by lemma 18 and corollary 17,

$$P(X_{2n})(i, i') \geq \frac{1}{\bar{a} \bar{b} \bar{C}(X_3)} (X_{2n+1} X_{2n+1}^\top)(i, i'),$$

so the non-zero entries of  $P(X_{2n})$  are bounded below by some constant  $c > 0$ .

We now define a binary relation on the set  $[1, p]$  by

$$i \mathcal{R} i' \Leftrightarrow X_0 X_0^\top(i, i') > 0 \Leftrightarrow \exists j \in [1, q], X_0(i, j) X_0(i', j) > 0.$$

The matrix  $X_0 X_0^\top$  is symmetric with positive diagonal (since on each line,  $X_0$  has at least a positive entry), so the relation  $\mathcal{R}$  is symmetric and reflexive. Call  $I_1, \dots, I_r$  the connected components of the graph  $G$  associated to  $\mathcal{R}$ , and  $d$  the maximum of their diameters. For each  $k$ , set  $J_k = \{j \in [1, q] : \exists i \in I_k : X_0(i, j) > 0\}$ .

**Lemma 24.** *The sets  $J_1, \dots, J_r$  form a partition of  $[1, q]$  and the support of  $X_0$  is contained in  $I_1 \times J_1 \cup \dots \cup I_r \times J_r$ . Therefore, the support of  $X_0 X_0^\top$  is contained in  $I_1 \times I_1 \cup \dots \cup I_r \times I_r$ , so one can get a block-diagonal matrix by permuting suitably the lines of  $X_0$ .*

*Proof.* By assumption, the sum of the entries of  $X_0$  on any row or any column is positive.

Given  $k \in [1, r]$  and  $i \in I_k$ , there exists  $j \in [1, q]$  such that  $X_0(i, j) > 0$ , so  $J_k$  is not empty.

Fix now  $j \in [1, q]$ . There exists  $i \in [1, p]$  such that  $X_0(i, j) > 0$ . Such an  $i$  belongs to some connected component  $I_k$ , and  $j$  belongs to the corresponding  $J_k$ . If  $j$  also belongs to  $J_{k'}$ , then  $X_0(i', j) > 0$  for some  $i' \in I_{k'}$ , so  $X_0 X_0^\top(i, i') \geq X_0(i, j) X_0(i', j) > 0$ , hence  $i$  and  $i'$  belong to the connected component of  $G$ , so  $k' = k$ .

The other statements follow.  $\square$

**Lemma 25.** *Let  $i \in I_k$  and  $i' \in I_{k'}$ . Set  $P_m = P(X_m)$  for all  $m \geq 0$ . Let  $n \geq 1$ , and  $M_n = P_{2n+2d-2} \cdots P_{2n+2} P_{2n}$ . Then*

$$\begin{aligned} M_n(i, i') &\geq c^d && \text{if } k = k'. \\ M_n(i, i') &= 0 && \text{if } k \neq k'. \end{aligned}$$

*Proof.* Indeed,

$$M_n(i, i') = \sum_{1 \leq i_1, \dots, i_{d-1} \leq p} P_{2n+2d-2}(i, i_1) P_{2n+2d-4}(i_1, i_2) \cdots P_{2n+2}(i_{d-2}, i_{d-1}) P_{2n}(i_{d-1}, i').$$

If  $k \neq k'$ , all these products are 0, since no path can connect  $i$  and  $i'$  in the graph  $G$ .

If  $k = k'$ , one can find a path  $i = i_0, \dots, i_\ell = i'$  in the graph  $G$  with length  $\ell \leq d$ . Setting  $i_{\ell+1} = \dots = i_d$  if  $\ell < d$ , we get

$$P_{2n+2d-2}(i, i_1) P_{2n+2d-4}(i_1, i_2) \cdots P_{2n+2}(i_{d-2}, i_{d-1}) P_{2n}(i_{d-1}, i') \geq c^d.$$

The result follows.  $\square$

Keep the notations of the last lemma. Then for every  $n \geq 1$ ,  $R(X_{2n+2d}) = M_n R(X_{2n})$ . For each  $k \in [1, r]$ , lemma 8 applied to the submatrix  $(M_n(i, i'))_{i, i' \in I_k}$  and the vector  $L_{I_k}(X_{2n}) = (R_i(X_{2n}))_{i \in I_k}$  yields

$$\text{diam}(L_{I_k}(X_{2n+2d})) \leq (1 - c^d) \text{diam}(L_{I_k}(X_{2n})).$$

But lemma 8 applied to the submatrix  $(P(X_{2n})(i, i'))_{i, i' \in I_k}$  shows that the intervals

$$\left[ \min_{i \in I_k} R_i(X_{2n}), \max_{i \in I_k} R_i(X_{2n}) \right]$$

indexed by  $n \geq 1$  form a non-increasing sequence. Therefore, each sequence  $(R_i(X_{2n}))$  tends to a limit which does not depend on  $i \in I_k$ , and the speed of convergence is at least geometric.

Call  $\lambda_k$  this limit. By lemma 24, we have for every  $n \geq 1$ ,

$$\sum_{i \in I_k} a_i R_i(X_{2n}) = \sum_{(i, j) \in I_k \times J_k} X_{2n}(i, j) = \sum_{j \in J_k} X_{2n}(i, j) = \sum_{j \in J_k} b_j$$

Passing to the limit yields

$$\lambda_k \sum_{i \in I_k} a_i = \sum_{j \in J_k} b_j,$$

whereas the assumption that  $\Gamma$  contains some matrix  $S$  having the same support as  $X_0$  yields

$$\sum_{i \in I_k} a_i = \sum_{(i, j) \in I_k \times J_k} S(i, j) = \sum_{j \in J_k} b_j.$$

Thus  $\lambda_k = 1$ .

We have proved that each sequence  $(R_i(X_{2n}))_{n \geq 0}$  tends to 1 with at least geometric rate. The same arguments work for the sequences  $(C_j(X_{2n+1}))_{n \geq 0}$ . Therefore, each infinite product  $R_i(X_0)R_i(X_2) \cdots$  or  $C_j(X_1)C_j(X_3) \cdots$  converges at an at least geometric rate. The convergence of the sequence  $(X_n)_{n \geq 0}$  with at a least geometric rate follows.

Moreover, call  $\alpha_i$  and  $\beta_j$  the inverses of the infinite products  $R_i(X_0)R_i(X_2) \cdots$  and  $C_j(X_1)C_j(X_3) \cdots$  and  $X_\infty$  the limit of  $(X_n)_{n \geq 0}$ . Then  $X_\infty(i, j) = \alpha_i \beta_j X_0(i, j)$ , so  $X_\infty$  belongs to the set  $\Delta_p X_0 \Delta_q$ . As noted in the introduction, we have also  $X_\infty \in \Gamma$ . It remains to prove that  $X_\infty$  is the only matrix in  $\Gamma \cap \Delta_p X_0 \Delta_q$  and the only matrix which achieves the least upper bound of  $D(Y||X_0)$  over all  $Y \in \Gamma(X_0)$ .

Let  $E_{X_0}$  be the vector space of all matrices in  $\mathcal{M}_{p,q}(\mathbf{R})$  which are null on  $\text{Supp}(X_0)^c$  (which can be identified canonically with  $\mathbf{R}^{\text{Supp}(X_0)}$ ), and  $E_{X_0}^+$  be the convex subset of all non-negative matrices in  $E_{X_0}$ . The subset  $E_{X_0}^{+*}$  of all matrices in  $E_{X_0}$  which are positive on  $\text{Supp}(X_0)^c$ , is open in  $E_{X_0}$ , dense in  $E_{X_0}^+$  and contains  $X_\infty$ . Consider the map  $f_{X_0}$  from  $E_{X_0}^+$  to  $\mathbf{R}$  defined by

$$f_{X_0}(Y) = \sum_{(i, j) \in \text{Supp}(X_0)} Y(i, j) \ln \frac{Y(i, j)}{X_0(i, j)},$$

with the convention  $t \ln t = 0$ . This map is strictly convex since the map  $t \mapsto t \ln t$  from  $\mathbf{R}_+$  to  $\mathbf{R}$  is. Its differential at any point  $Y \in E_{X_0}^{+*}$  is given by

$$df_{X_0}(Y)(H) = \sum_{(i, j) \in \text{Supp}(X_0)} \left( \ln \frac{Y(i, j)}{X_0(i, j)} + 1 \right) H(i, j).$$

Now, if  $Y_0$  is any matrix in  $\Gamma \cap \Delta_p X_0 \Delta_q$  (including the matrix  $X_\infty$ ), the quantities  $\ln(Y(i, j)/X_0(i, j))$  can be written  $\lambda_i + \mu_j$ . Thus for every matrix  $H \in E(X_0)$  with null row-sums and column-sums,  $df_{X_0}(Y_0)(H) = 0$ , hence the restriction of  $f_{X_0}$  to  $\Gamma(X_0)$  has a strict global minimum at  $Y_0$ . The proof is complete.



**The case of positive matrices.** The proof of the convergence at an at least geometric rate can be notably simplified when  $X_0$  has only positive entries. In this case, Fienberg [5] used geometric arguments to prove the convergence of the iterated proportional fitting procedure at an at least geometric rate. We sketch another proof using the observation made by Fienberg that the ratios

$$\frac{X_n(i, j)X_n(i', j')}{X_n(i, j')X_n(i', j)}$$

are independent of  $n$ , since they are preserved by the transformations  $T_R$  and  $T_C$ . Call  $\kappa$  the least of these positive constants. Using corollary 17, one checks that the average of the entries of  $X_n$  on each row or column remains bounded below by some constant  $\gamma > 0$ . Thus for every location  $(i, j)$  and  $n \geq 1$ , one can find two indexes  $i' \in [1, p]$  and  $j' \in [1, q]$  such that  $X_n(i', j) \geq \gamma$  and  $X_n(i, j') \geq \gamma$ , so

$$X_n(i, j) \geq X_n(i, j')X_n(i', j) \geq \kappa X_n(i, j')X_n(i', j) \geq \kappa \gamma^2.$$

This shows that the entries of the matrices  $X_n$  remain bounded away from 0, so the ratios  $X_n(i, j)/b_j$  and  $X_n(i, j)/a_i$  are bounded below by some constant  $c > 0$  independent of  $n \geq 1$ ,  $i$  and  $j$ . Set

$$\rho_n = \frac{\overline{R}(X_n)}{\underline{R}(X_n)} \text{ if } n \text{ is even, } \rho_n = \frac{\overline{C}(X_n)}{\underline{C}(X_n)} \text{ if } n \text{ is odd.}$$

For every  $n \geq 1$ , the equalities

$$C_j(X_{2n+1}) = \sum_{i=1}^p \frac{X_{2n}(i, j)}{b_j} \frac{1}{R_i(X_{2n+1})}$$

and lemma 8 yields

$$\overline{R}(X_{2n})^{-1} \leq (1-c)\overline{R}(X_{2n})^{-1} + c\underline{R}(X_{2n})^{-1} \leq C_j(X_{2n+1}) \leq (1-c)\underline{R}(X_{2n})^{-1} + c\overline{R}(X_{2n})^{-1}.$$

Thus,

$$\begin{aligned} \rho_{2n+1} - 1 &= \frac{\overline{C}(X_{2n+1}) - \underline{C}(X_{2n+1})}{\underline{C}(X_{2n+1})} \\ &\leq \frac{(1-2c)(\underline{R}(X_{2n})^{-1} - \overline{R}(X_{2n})^{-1})}{\overline{R}(X_{2n})^{-1}} = (1-2c)(\rho_{2n} - 1). \end{aligned}$$

We prove the inequality  $\rho_{2n} - 1 \leq (1-2c)(\rho_{2n-1} - 1)$  in the same way. Hence  $\rho_n \rightarrow 1$  at an at least geometric rate. The result follows by corollary 17.

## 7 Proof of theorem 3

We now assume that  $\Gamma$  contains some matrix with support included in  $\text{Supp}(X_0)$ .

### 7.1 Asymptotic behavior of the sequences $(R(X_n))$ and $(C(X_n))$ .

The first item of corollary 22 yields the convergence of the infinite product

$$\prod_i R_i(X_0)^{a_i} \times \prod_j C_j(X_1)^{b_j} \times \prod_i R_i(X_2)^{a_i} \times \prod_j C_j(X_3)^{b_j} \times \dots$$

Set  $g(t) = t - 1 - \ln t$  for every  $t > 0$ . Using the equalities

$$\forall n \geq 1, \sum_{i=1}^p a_i R_i(X_{2n}) = \sum_{j=1}^q b_j C_j(X_{2n-1}) = 1,$$

we derive the convergence of the series

$$\sum_i a_i g(R_i(X_0)) + \sum_j b_j g(C_j(X_1)) + \sum_i a_i g(R_i(X_2)) + \sum_j b_j g(C_j(X_3)) + \dots$$

But  $g$  is null at 1, positive everywhere else, and tends to infinity at  $0+$  and at  $+\infty$ . By positivity of the  $a_i$  and  $b_j$ , we get the convergence of all series

$$\sum_{n \geq 0} g(R_i(X_{2n})) \text{ and } \sum_{n \geq 0} g(C_j(X_{2n+1}))$$

and the convergence of all sequences  $(R_i(X_{2n}))_{n \geq 0}$  and to  $(C_j(X_{2n+1}))_{n \geq 0}$  towards 1. But  $g(t) \sim (t-1)^2/2$  as  $t \rightarrow 1$ , so the series  $\sum_n (R_i(X_{2n}) - 1)^2$  and  $\sum_{n \geq 0} (C_j(X_{2n+1}) - 1)^2$  converge.

We now use a quantity introduced by Bregman [2] and called  $L_1$ -error by Pukelsheim [11]. For every  $X \in \Gamma_1$ , set

$$\begin{aligned} e(X) &= \sum_{i=1}^p \left| \sum_{j=1}^q X(i, j) - a_i \right| + \sum_{j=1}^q \left| \sum_{i=1}^p X(i, j) - b_j \right| \\ &= \sum_{i=1}^p a_i |R_i(X) - 1| + \sum_{j=1}^q b_j |C_j(X) - 1|. \end{aligned}$$

The convexity of the square function yields

$$\frac{e(X)^2}{2} \leq \sum_{i=1}^p a_i (R_i(X) - 1)^2 + \sum_{j=1}^q b_j (C_j(X) - 1)^2.$$

Thus the series  $\sum_n e(X_n)^2$  converges. But the sequence  $(e(X_n))_{n \geq 1}$  is non-increasing (the proof of this fact is recalled below). Therefore, for every  $n \geq 1$ ,

$$0 \leq \frac{n}{2} e(X_n)^2 \leq \sum_{n/2 \leq k \leq n} e(X_k)^2.$$

Convergences  $ne(X_n)^2 \rightarrow 0$ ,  $\sqrt{n}(R_i(X_n) - 1) \rightarrow 0$  and  $\sqrt{n}(C_j(X_n) - 1) \rightarrow 0$  follow.

To check the monotonicity of  $(e(X_n))_{n \geq 1}$ , note that  $T_R(X) \in \Gamma_R$  for every  $X \in \Gamma_C$ , so

$$\begin{aligned} e(T_R(X)) &= \sum_{j=1}^q \left| \sum_{i=1}^p X(i, j) R_i(X)^{-1} - b_j \right| \\ &= \sum_{j=1}^q \left| \sum_{i=1}^p X(i, j) (R_i(X)^{-1} - 1) \right| \\ &\leq \sum_{i=1}^p \sum_{j=1}^q X(i, j) |R_i(X)^{-1} - 1| \\ &= \sum_{i=1}^p a_i R_i(X) |R_i(X)^{-1} - 1| \\ &= e(X). \end{aligned}$$

In the same way,  $e(T_C(Y)) \leq e(Y)$  for every  $Y \in \Gamma_R$ .

## 7.2 Convergence and limit of $(X_n)$

Since  $\Gamma(X_0)$  is not empty, we can fix a matrix  $S_0 \in \Gamma(X_0)$  with support as large as possible, like in remark 23 (at the end of section 5).

Let  $L$  be a limit point of the sequence  $(X_n)_{n \geq 0}$ , so  $L$  is the limit of some subsequence  $(X_{\varphi(n)})_{n \geq 0}$ . As noted in the introduction,  $\text{Supp}(L) \subset \text{Supp}(X_0)$ . But for every  $i \in [1, p]$  and  $j \in [1, q]$ ,  $R_i(L) = \lim R_i(X_{\varphi(n)}) = 1$  and  $C_j(L) = \lim C_j(X_{\varphi(n)}) = 1$ . Hence  $L \in \Gamma(X_0)$ . Corollary 22 yields the inclusion  $\text{Supp}(S_0) \subset \text{Supp}(L)$  hence for every  $S \in \Gamma(X_0)$ ,  $\text{Supp}(S) \subset \text{Supp}(S_0) \subset \text{Supp}(L) \subset \text{Supp}(X_0)$ , so the quantities  $F_S(X_0)$  and  $F_S(L)$  are positive.

By lemma 21, the ratios  $F_S(X_{\varphi(n)})/F_S(X_0)$  do not depend on  $S \in \Gamma(X_0)$ , so by continuity of  $F_S$ , the ratio  $F_S(L)/F_S(X_0)$  does not depend on  $S \in \Gamma(X_0)$ . But by lemma 20,

$$\log_2 \frac{F_S(L)}{F_S(X_0)} = \log_2 \frac{F_S(S)}{F_S(X_0)} - \log_2 \frac{F_S(S)}{F_S(L)} = D(S||X_0) - D(S||L),$$

and  $D(S||L) \geq 0$  with equality if and only if  $S = L$ . Therefore,  $L$  is the only element achieving the greatest lower bound of  $D(S||X_0)$  over all  $S \in \Gamma(X_0)$ .

$$L = \arg \min_{S \in \Gamma(X_0)} D(S||X_0).$$

We have proved the unicity of the limit point of the sequence  $(X_n)_{n \geq 0}$ . By compactity of  $\Gamma(X_0)$ , the convergence follows.

**Remark 26.** *Actually, one has  $\text{Supp}(S_0) = \text{Supp}(L)$ . Indeed, theorem 3 shows that for every  $(i, j) \in \text{Supp}(X_0) \setminus \text{Supp}(S_0)$ ,  $X_n(i, j) \rightarrow 0$  as  $n \rightarrow +\infty$ . This fact could be retrived by using the same arguments as in the proof of theorem 1 to show that on the set  $\Gamma(X_0)$ , the linear form  $X \mapsto X(i_0, j_0)$  coincides with some linear combination of the affine forms  $X \mapsto R_i(X) - 1$ ,  $i \in [1, p]$ , and  $X \mapsto C_j(X) - 1$ ,  $j \in [1, q]$ .*

## 8 Proof of theorems 4 and 5

We recall that neither proof below uses the assumption that  $\Gamma(X_0)$  is empty.

### 8.1 Proof of theorem 4

**Convergence of the sequences  $(R(X_{2n}))$  and  $(C(X_{2n+1}))$ .** By lemma 18 and corollary 17, we have for every  $n \geq 1$ ,  $R(X_{2n+2}) = P(X_{2n})R(X_{2n})$ , where  $P(X_{2n})$  is a stochastic matrix such that for every  $i$  and  $k$  in  $[1, p]$ ,

$$P(X_{2n})(i, i) \geq \frac{\underline{a}}{\bar{b} \bar{C}(X_{2n+1})_q} \geq \frac{\underline{a} \underline{R}(X_2)}{\bar{b} q}$$

and

$$P(X_{2n})(k, i) \leq (\bar{a}/\underline{a})P(X_{2n})(i, k).$$

The sequence  $(P(X_{2n}))_{n \geq 0}$  satisfies the assumption of corollary 12 and theorem 6, so any one of these two results ensures the convergence of the sequence  $(R(X_{2n}))_{n \geq 0}$ . By corollary 17, the entries of these vectors stay in the interval  $[\underline{R}(X_2), \bar{R}(X_2)]$ , so the limit of each entry is positive. The same arguments show that the sequence  $(C(X_{2n+1}))_{n \geq 0}$  also converges to some vector with positive entries.

**Relations between the components of the limits, and block structure.** Denote by  $\lambda_1 < \dots < \lambda_r$  the different values of the limits of the sequences  $(R_i(X_{2n}))_{n \geq 0}$ , and by  $\mu_1 > \dots > \mu_s$  the different values of the limits of the sequences  $(C_j(X_{2n+1}))_{n \geq 0}$ . The values of these limits will be precised later. Consider the sets

$$I_k = \{i \in [1, p] : \lim R_i(X_{2n}) = \lambda_k\} \text{ for } k \in [1, r],$$

$$J_l = \{j \in [1, q] : \lim C_j(X_{2n+1}) = \mu_l\} \text{ for } l \in [1, s].$$

When  $(i, j) \in I_k \times J_l$ , the sequence  $(R_i(X_{2n})C_j(X_{2n+1}))_{n \geq 0}$  converges to  $\lambda_k \mu_l$ . If  $\lambda_k \mu_l > 1$ , this entails the convergence to 0 of the sequence  $(X_n(i, j))_{n \geq 0}$  with a geometric rate; and if  $\lambda_k \mu_l < 1$ , this entails the nullity of all  $X_n(i, j)$  (otherwise the sequence  $(X_n(i, j))_{n \geq 0}$  would go to infinity). But for all  $n \geq 1$ ,  $R_i(X_{2n}) = 1$  and  $C_j(X_{2n+1}) = 1$ , so at least one entry of the matrices  $X_n$  on each line or column does not converge to 0. This forces the equalities  $s = r$  and  $\mu_k = \lambda_k^{-1}$  for every  $k \in [1, r]$ .

**Convergence of the sequences  $(X_{2n})$  and  $(X_{2n+1})$ .** Let  $L$  be any limit point of the sequence  $(X_{2n})_{n \geq 0}$ , so  $L$  is the limit of some subsequence  $(X_{2\varphi(n)})_{n \geq 0}$ . By definition of  $a'$ ,  $R_i(L) = \lim R_i(X_{2\varphi(n)}) = a'_i/a_i$  for every  $i \in [1, p]$ . Moreover,  $\text{Supp}(L) \subset \text{Supp}(X_0)$ , so  $L$  belongs to  $\Gamma(a', b, X_0)$ . By lemma 21, the ratios  $F_S(X_{2\varphi(n)})/F_S(X_0)$  do not depend on  $S \in \Gamma(X_0)$ , so by continuity of  $F_S$ , the ratio  $F_S(L)/F_S(X_0)$  does not depend on  $S \in \Gamma(X_0)$ . But by lemma 20,

$$\log_2 \frac{F_S(L)}{F_S(X_0)} = \log_2 \frac{F_S(S)}{F_S(X_0)} - \log_2 \frac{F_S(S)}{F_S(L)} = D(S||X_0) - D(S||L),$$

and  $D(S||L) \geq 0$  with equality if and only if  $S = L$ . Therefore,  $L$  is the unique matrix achieving the greatest lower bound of  $D(S||X_0)$  over all  $S \in \Gamma(a', b, X_0)$ .

$$L = \arg \min_{S \in \Gamma(X_0)} D(S||X_0).$$

We have proved the uniqueness of the limit point of the sequence  $(X_{2n})_{n \geq 0}$ . By compactness of  $\Gamma(a', b, X_0)$ , the convergence follows. The same arguments show that the sequence  $(X_{2n+1})_{n \geq 0}$  converges to the unique matrix achieving the greatest lower bound of  $D(S||X_0)$  over all  $S \in \Gamma(a, b', X_0)$ .

**Formula for  $\lambda_k$ .** We know that the sequence  $(X_n(i, j))_{n \geq 0}$  converges to 0 whenever  $i \in I_k$  and  $j \in J_l$  with  $k \neq l$ . Thus the support of  $L = \lim X_{2n}$  is contained in  $I_1 \times J_1 \cup \dots \cup I_r \times J_r$ . But  $L$  belongs to  $\Gamma(a', b, X_0)$ , so for every  $k \in [1, r]$

$$\lambda_k a(I_k) = \sum_{i \in I_k} a'_i = \sum_{(i, j) \in I_k \times J_k} L(i, j) = \sum_{j \in J_k} b_j = b(J_k).$$

**Properties of matrices in  $\Gamma(a', b, X_0)$  and  $\Gamma(a, b', X_0)$ .** Let  $S \in \Gamma(a, b', X_0)$ .

Let  $k \in [1, r-1]$ ,  $A_k = I_1 \cup \dots \cup I_k$  and  $B_k = J_{k+1} \cup \dots \cup J_r$ . We already know that  $X_0$  is null on  $A_k \times B_k$ , so  $S$  is also null on this set. Moreover, for every  $l \in [1, r]$ ,

$$a(I_l) = \lambda_l^{-1} b(J_l) = \sum_{j \in J_l} \lambda_l^{-1} b_j = \sum_{j \in J_l} b'_j = b'(J_l).$$

Summation over all  $l \in [1, k]$  yields  $a(A_k) = b'(B_k^c)$ . Hence by theorem 1  $S$  is null on the set  $A_k^c \times B_k^c = (J_{k+1} \cup \dots \cup I_r) \times (J_1 \cup \dots \cup J_k)$ .

This shows that the support of  $S$  is included in  $I_1 \times J_1 \cup \dots \cup I_r \times J_r$ . This block structure and the equalities  $a'_i/a_i = b_j/b'_j = \lambda_k$  whenever  $(i, j) \in I_k \times J_k$  yield the equality  $D_1 S = S D_2$ . This matrix has the same support as  $S$ . Moreover, its  $i$ -th row is  $a'_i/a_i$  times the  $i$ -th row of  $S$ , so its  $i$ -th row-sum is  $a'_i/a_i \times a_i = a'_i$ ; in the same way its  $j$ -th column is  $b_j/b'_j$  times the  $j$ -th column of  $S$ , so its  $j$ -th column sum is  $b_j/b'_j \times b'_j = b_j$ . As symmetric conclusions hold for every matrix in  $\Gamma(a', b, X_0)$ , the proof is complete.

## 8.2 Proof of theorem 5

Let  $k \in [1, r]$ ,  $P = [1, p] \setminus (I_1 \cup \dots \cup I_{k-1})$ ,  $Q = [1, q] \setminus (J_1 \cup \dots \cup J_{k-1})$ . Fix  $S \in \Gamma(a', b, X_0)$  (we know by theorem 4 that this set is not empty).

If  $k = r$ , then  $P = I_r$  and  $Q = J_r$ . As  $a'_i = a_i b(J_r)/a(I_r)$  for every  $i \in I_r$ , we have  $a'(I_r) = b(J_r)$  and  $a'_i/a'(I_r) = a_i b(J_r)/a(I_r)$  for every  $i \in I_r$ . Therefore, the matrix  $(S(i, j)/a'(I_r))$  is a solution of the restricted problem associated to the marginals  $a(\cdot|P) = (a_i/a(I_r))_{i \in P}$ ,  $b(\cdot|Q) = (b_j/b(Q))_{j \in Q}$  and to the initial condition  $(X_0(i, j))_{(i, j) \in P \times Q}$ .

If  $k < r$ , then  $P = I_k \cup \dots \cup I_r$  and  $Q = J_k \cup \dots \cup J_r$ . Let  $A_k = I_k$  and  $B_k = J_{k+1} \cup \dots \cup J_r$ . By theorem 4, the matrix  $X_0$  is null on product  $A_k \times B_k$ . Moreover, the inequalities  $\lambda_1 < \dots < \lambda_r$  and  $a(I_l) > 0$  for every  $l \in [1, r]$  yield

$$b(Q) = \sum_{l=k}^r b(J_l) = \sum_{l=k}^r \lambda_l a(I_l) > \lambda_k \sum_{l=k}^r a(I_l) = \lambda_k a(P),$$

so

$$\frac{a(A_k|P)}{b(Q \setminus B_k|Q)} = \frac{a(I_k)/a(P)}{b(J_k)/b(Q)} = \lambda_k^{-1} \frac{b(Q)}{a(P)} > 1.$$

Hence  $A_k \times B_k$  is a cause of incompatibility of the restricted problem associated to the marginals  $a(\cdot|P) = (a_i/a(P))_{i \in P}$ ,  $b(\cdot|Q) = (b_j/b(Q))_{j \in Q}$  and to the initial condition  $(X_0(i, j))_{(i, j) \in P \times Q}$ .

Now, assume that  $X_0$  is null on some subset  $A \times B$  of  $P \times Q$ . Then  $S$  is also null on  $A \times B$ , so for every  $l \in [k, r]$ ,

$$\lambda_k a(A \cap I_l) \leq \lambda_l a(A \cap I_l) = a'(A \cap I_l) = S((A \cap I_l) \times ((Q \setminus B) \cap J_l)) \leq b((Q \setminus B) \cap J_l).$$

Summing this inequalities over all  $l \in [k, r]$  yields  $\lambda_k a(A) \leq b(Q \setminus B)$ , so

$$\frac{a(A)}{b(Q \setminus B)} \leq \lambda_k^{-1} = \frac{a(I_k)}{b(I_k)} = \frac{a(A_k)}{b(Q \setminus B_k)}.$$

Moreover, if equality holds in the last inequality, then for every  $l \in [k, r]$ ,

$$\lambda_k a(A \cap I_l) = \lambda_l a(A \cap I_l) = b((Q \setminus B) \cap J_l).$$

This yields  $A \cap I_l = (Q \setminus B) \cap J_l = \emptyset$  for every  $l \in [k+1, r]$ , thus  $A \subset I_k = A_k$  and  $Q \setminus B \subset I_k$ , namely  $B \supset B_k$ . The proof is complete.

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## References

- [1] M. Bacharach, *Estimating Nonnegative Matrices from Marginal Data*. International Economic Review, **6-3**, p. 294–310 (1965).
- [2] L.M. Bregman, *Proof of the convergence of Sheleikhovskii's method for a problem with transportation constraints*. USSR Computational Mathematics and Mathematical Physics **7-1**, Pages 191-204 (1967).
- [3] J.B. Brown, P.J. Chase, A.O. Pittenger *Order independence and factor convergence in iterative scaling*. Linear Algebra and its Applications **190**, p 1–39 (1993).
- [4] I. Csiszár, *I-divergence geometry of probability distributions and minimization problems*. Annals of Probability **3-1**, p 146–158 (1975).
- [5] S. Fienberg, *An iterative procedure for estimation in contingency tables*, Annals of Mathematical Statistics **41-3**, p 907–917 (1970).
- [6] C. Gietl - F. Reffel, *Accumulation points of the iterative scaling procedure*, Metrika **73-1**, p783–798 (2013).
- [7] C.T. Ireland, S. Kullback, *Contingency tables with given marginals*, Biometrika **55-1**, p179–188 (1968).
- [8] J. Kruithof, *Telefoonverkeers rekening* (Calculation of telephone traffic). De Ingenieur 52, pp. E15–E25. Krupp, R. S (1937)
- [9] J. Lorenz, *A stabilization theorem for dynamics of continuous opinions*. Physica A, Statistical Mechanics and its Applications, **355-1**, pp. 217-223 (2005).
- [10] O. Pretzel, *Convergence of the iterative scaling procedure for non-negative matrices*. Journal of the London Mathematical Society **21**, p 379–384 (1980).
- [11] F. Pukelsheim, *Biproportional matrix scaling and the Iterative Proportional Fitting procedure*. Annals of Operations Research **215** 269-283 (2014).
- [12] R. Sinkhorn, *Diagonal Equivalence to Matrices with Prescribed Row and Column Sums*. American Mathematical Monthly **74-4**, p 402-405 (1967).
- [13] B. Touri, *Product of Random Stochastic Matrices and Distributed Averaging*. Springer Thesis (2012).
- [14] B. Touri and A. Nedić, *On Backward Product of Stochastic Matrices*. Automatica **48-8**, 1477–1488 (2012).
- [15] B. Touri and A. Nedic, *Alternative Characterization of Ergodicity for Doubly Stochastic Chains* Proceedings of the 50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC), Orlando, Florida, December 2011, pp. 5371-5376.
- [16] B. Touri and A. Nedić, *On ergodicity, infinite flow and consensus in random models*. IEEE Transactions on Automatic Control **56-7** 1593-1605 (2011).
- [17] R. Webster, *Convexity*. Oxford University Press (1994).